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Do Some Firms Persistently Outperform ?

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DO SOME FIRMS PERSISTENTLY OUTPERFORM?

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Abstract

This study analyses persistence in growth rates of the entire population of Dutch manufacturing firms. Previous literature on firm growth rates shows that extreme growth events are likely to be negatively correlated over time. A rebound effect following an extreme growth event questions the existence of persistent outperformers, indicated by a positive correlation over time. By supplementing the quantile regression analyses with transition probability matrices, our study shows that 'bouncing' firms co-exist with persistent outperformers. This result is robust if we exclude firms involved in acquisitions or spin offs. Differentiating among different size classes, we find that the existence of persistent outperformers is especially pronounced in micro firms. We interpret this finding as supporting the notion of a Schumpeter Mark I regime, with small firms displaying strong heterogeneity in their growth patterns, versus a Schumpeter Mark II regime, with large firms displaying less heterogeneity of growth.

Keywords: firm growth; heterogeneity; persistence, transition probability matrices; quantile regression.
JEL codes: L11, L25

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1. Introduction

This study analyses the growth rate distributions of the entire population of manufacturing firms in the Netherlands, in the period 1994 to 2004. In particular, we examine whether there is persistence in growth rates in terms of firms that persistently outperform or underperform.

A vast economics and management literature emphasizes that there are persistent asymmetries among firms in terms of size, innovation and productivity. The existence of heterogeneous firms with different capabilities results in persistent heterogeneous firm performance (especially in relation to corporate growth and profitability). There are firms that persistently perform better or worse than others - or, in other words, there are persistent outperformers and underperformers.

As Dosi and Nelson (2009, p. 45) point out, the possible explanations for differences in corporate performance include differences in the ability to innovate and different production efficiencies. With regard to the ability to innovate, there is a growing empirical literature showing that firms have very different capabilities to innovate, resulting in a small number of firms in each sector (referred as “great innovators”) accounting for the majority of the innovative output, within a large group of minor innovators, and an even larger group of non-innovators (Geroski et al., 1997; Cefis and Orsenigo, 2001). Furthermore, these different abilities to innovate across firms are persistent over time: there are “systematic” innovators that are able to innovate continuously (as opposed to “occasional” innovators that may produce an innovation once in a while, but with no continuity) and persistent non-innovators (Malerba and Orsenigo, 1996; Bottazzi et al, 2001; Cefis, 2003; Peters, 2009; Raymond at al. 2009).

In terms of heterogeneity in production efficiency, there is a robust evidence that production efficiency differs widely and persistently across firms and across plants (Baily and Chakrabarty, 1985; Rumelt, 1991; Baldwin, 1995; Jensen and McGuckin, 1997; Bartelsman and Doms, 2000; Dosi, 2007). These asymmetries can be found at relatively high levels of sectoral aggregation and do not depend on differences in relative factor intensities (Syverson, 2004; Bottazzi et al., 2007; Dosi, 2007). Evolutionary economists emphasize that differences in firm productivity should be expected given the idiosyncratic routines, capabilities and competencies of firms and their different learning processes.

The persistently higher innovative capability and/or persistently greater efficiency should translate into persistently higher firm performance, and particularly persistently higher profitability and/or corporate growth. Substantial research effort has been devoted to examining profit persistence, and several empirical studies show that firms display persistent differences in profitability (Mueller, 1986 and 1990; Cubbin and Geroski, 1987; Glen et al., 2001; Goddard and Wilson, 1999; Cefis, 2003; Gschwandter, 2004; Dosi, 2007), that is, profits do not seem to converge to a common rate of return. Moreover, there is evidence indicating that the adjustment of profits to their firm-specific "permanent" values is generally quite rapid, although there is significant variability across countries (see, e.g., Geroski and Jacquemin, 1988; Droucopoulos and Lianos, 1993; Maruyama and Odagiri, 2002). However, it is difficult to say to what extent the observed persistence in profitability differentials reflects the persistence of differential "efficiency" levels which are not eroded away by the competitive process.

When a firm has good innovative capabilities and/or high production efficiency it might be expected that it would grow with some persistence and that firms that perform persistently worse than their competitors should have persistent negative or null relative growth rates if the market selection mechanism allows them to survive. There is robust evidence that corporate growth rates result in distributions with fat tails regardless of level of sectoral aggregation, country, and measures of size used (see among others for the US Stanley et al., 1996 and Bottazzi and Secchi, 2003; for Italy Bottazzi et al., 2002; and Bottazzi et al., 2003 ; for France Coad, 2007; for Austria Coad and Hölzl, 2009; and for Denmark Reichstein and Jensen, 2005).

These studies show that growth rate distributions are often quite stable over time and, if in a statistical sense they are not, their shape remains constant over time, always displaying fat tails where outperformers and underperformers are concentrated. The stability of the distributions, or the stability of the shape of the distribution, may be given either by the fact that there is an intra-distributional mobility of firms that substitutes firms formerly in the tails with new ones, in every period, or by the fact that firms remain in the same positions as time goes by.

It is this aspect that this paper addresses by analysing the growth rate distributions of the *entire* population of firms to investigate whether there are firms that grow persistently (positively or negatively) in relative terms, and whether there is intra-distributional mobility among firms as time passes. Among the studies that have empirically investigated the validity of Gibrat's Law, there are some that focus on the persistence of growth. In fact, finding persistence in growth rates is one way to prove that Gibrat's Law does not hold. Gibrat's Law implies the absence of any structure in growth processes since firm growth does not depend on firm size and follows a random path. In particular, Gibrat's Law asserts the absence of serial correlation in the error terms.

The first studies to focus on this topic regress current growth rates on lagged growth rates and find some persistence (Singh and Whittington, 1975; Dunne and Hughes, 1994, among others). Chesher (1979) was the first to introduce a first order, autoregressive structure in the error terms (the autoregressive coefficient was found to be significant and positive), aimed mainly at obtaining unbiased estimates of the autoregression coefficient of size (usually analysed to test the validity of Gibrat's Law). Nevertheless, Chesher's paper provides further motivation to study persistence in growth.

The empirical evidence on the persistence of growth rates is mixed and depends on the sub-sample analysed and the methodology used. When sub-samples that are homogeneous with respect to some factors (same sector and same age in Lotti et al., 2001; same technological regime in Almus and Nerlinger, 2000; etc.) are considered, we find generally nil or weak persistence in growth rates. Fotopoulos and Giotopoulos (*forthcoming*) divide a sample of Greek manufacturing firms according to firm age and size and find that there is persistence only in certain groups, namely micro, small, and young firms. As Reichstein et al. (2009) point out, the methodology also plays a role in determining whether firm growth rates show persistence. They claim that: "Gaussian statistics are unfit for studying firm growth" and that the results from studies that rely on them are misleading since they focus on central moments in the distribution. Even for studies that assume an exponential-like growth rate distribution, such as Stanley et al. (1996), Bottazzi et al. (2002, 2003, 2007), but symmetric distributions (in the case of Bottazzi et al. due to data limitations: only firms with more than 20 employees) and concentrate on the central moment of the conditional distribution (in particular, the median), persistence is underestimated.

Lotti et al. (2003), Coad (2007), Coad and Höltz (2009), and Reichstein et al. (2009) apply quantile regressions to study persistence (or serial correlation) in growth rates taking into consideration the entire distribution and focusing on different percentiles separately. Lotti et al. (2003) test whether Gibrat's Law holds for new entrants in a given industry by running a quantile autoregression of firm size, and find that departures from Gibrat's Law may be due to the higher growth rates experienced by small entrant firms immediately after start up. Coad (2007), using a quantile autoregression of firm growth rates, shows that small, fast-growing firms are likely to display negative growth autocorrelation, while larger firms will often achieve smoother growth patterns. Coad and Hölzl (2009) confirm that autocorrelation dynamics vary with firm size, and extend the previous findings to the case of micro firms, whose growth seems to be characterized by lumpy adjustment patterns. Reichstein et al. (2009) use quantile regression techniques to link firm growth rates to industrial and regional characteristics. Firm size again is found to exert a moderating influence on growth, but industry concentration and regional specialization seem to put a lower bound on the growth rate of large firms.

Our paper aims to analyse persistence in growth rates, especially in the tails of the distributions, in order to assess whether there are persistent outperformers and persistent underperformers. The contributions of this work are fourfold: first, we use the entire population of manufacturing firms (without any employee number threshold), not assuming that firm growth rate distributions are symmetric, but investigating especially the asymmetric tails. Also, we shed more light on the different patterns among manufacturing firms conditional on firm size classes which goes beyond most of the previous studies which generally focus on particular size classes (typically excluding micro and small firms). Second, we account for exit and entry in the firm populations, and analyse persistence in growth rates based on an unbalanced panel and not just surviving firms. Considering only surviving firms may introduce a bias since we exclude negative growth rates for those firms that eventually exit the market, and the usually greater growth rates of new-born firms. Third, we account for acquisitions and spin-offs, which means we can disentangle internal growth from external growth (the latter being due to acquisition activity). To the best of our knowledge, there are no other studies that consider acquisitions and spin-offs directly.[1] Fourth, we do not only apply quantile regressions, we also qualify the results obtained in the quantile regression by estimating Transition Probability Matrices (TPM). These matrices allow us to detect whether bouncing firms (experiencing alternately highly positive and highly negative growth rates) co-

[1] In Bottazzi et al. (2002, 2003, 2007) mergers and acquisitions (M&A) were considered indirectly, by considering any pair of firms that was merged or acquired during the time span of the study,as a unique "super-firm" along the whole span. In the present study, while firms that merged in a given year must always be excluded by the corresponding yearly subset of the pooled cross-section (since our dataset does not enable us to track merged firms over time), episodes of acquisition and spin-off are explicitly considered, first by including in and then excluding from the cross-section of a given year all the firms that have experienced such episodes in that year.

exist with persistent performers (experiencing persistent highly positive or highly negative growth).

The main result of this study questions the conclusions from previous studies that extreme growth events are negatively correlated over time. By supplementing the quantile regression analyses with TPM, our study shows that bouncing firms co-exist with persistent outperformers. This result is shown to be robust once firms who experienced acquisitions or spin-off are excluded. Furthermore, in differentiating among size classes, we find that the co-existence of bouncing and persistent outperformers is especially pronounced in micro firms. We interpret this as supporting the notion of a Schumpeterian Mark I, or entrepreneurial, regime, versus a Schumpeter Mark II, or routinized regime (Winter 1984; Malerba and Orsenigo 1996; Breschi et al., 2000). These notions refer to distinct technological regimes. In the first regime, innovation is driven by the entry of micro firms operating in a technologically uncertain environment. Hence, the payoffs from R&D are highly uncertain with some firms catching on to a promising innovation path or business model, and other firms betting on a technological dead-end or failing business model. In the second regime, innovation stems primarily from large firms operating in a technologically more stable environment. Here, innovation rates are expected to be less heterogeneous among firms as R&D is spread across many more innovations and longer time horizons. Thus, it can be argued that the notions of Schumpeter Mark I and Schumpeter Mark II regimes are consistent with our finding that the persistence of extreme growth events is most pronounced for micro firms, and much less so for larger firms.

The paper is organized as follows. Section 2 describes the data and the variables in our analysis and Section 3 discusses the methodology. Section 4 presents the results of the graphical analysis and Section 5 presents the results of the regression analysis. Both sets of results are compared to those obtained in the previous literature. Section 6 makes a careful analysis of the quantile regression results and raises some doubts about the previous interpretations of the quantile regression results in the literature. Section 7 estimates the TPM and discusses the results. The analysis of the internal growth versus external growth is carried out in Section 8 and Section 9 concludes.

2. Data and Variables

The data in this paper were collected by the Centraal Bureau voor de Statistiek (CBS) and stem from the Business Register of enterprises. The Business Register (BR) database includes the entire population of firms registered for fiscal purposes in the Netherlands in the year considered. The database reports detailed information on the sector of the company, at the 5-digit SBI (the Dutch standard industry classification) level, number of employees and dates of entry and exit of firms in the market. The definition of entry and exit excludes changes in the firm's sector of activity; when this occurs, the firm is regarded as a continuing firm. Furthermore, the BR provides information on different types of exit, distinguishing between exits due to failure, to merger, to acquisition, and to radical restructuring. Our observation period covers the years 1994 to 2004. For each year, we selected all the manufacturing firms present in the BR. The population includes firms with zero employees, referred to as self-employment.

In this study, the main variables of interest are firm size and growth rate. We chose to analyse the behaviour for every firm, of the logarithm of firm size relative to the industry average, i.e., of the variable

$$s_i(t) = \ln\left(S_i(t) / \overline{S}_J(t)\right) \tag{1}$$

where $\overline{S}_J(t)$ represents the size geometric mean across all firms that at each time t belong to the same industry J to which firm i belongs. This is equivalent to

$$s_i(t) = \ln\left(S_i(t)\right) - \frac{1}{N_J} \sum_{j \in J} \ln\left(S_j(t)\right) \tag{2}$$

The relevant industry J for each firm is defined at the 3 digit SBI level. The new rescaled log variables represent deviations from the industry average (at the 3 digit level) for each firm. The use of the proportion of size $s_{ij}(t)$ as our basic variable, rather than plain size $S_j(t)$, or its logarithmic form, has important advantages:

i) the new variable controls for size differentials across industries at the 3 digit level;

ii) it controls for differences in sectoral growth rates;

iii) it removes possible common shocks and more general common factors in the economy such as business cycle and inflation;

iv) it has the advantage that it can be used to characterize distributions whenever the number of firms changes over time, and therefore provides an easy way to compare distributions with different numbers of observations.

The growth rate of firm size is defined as the difference in the logarithmic proportional size between two consecutive years, namely:

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

and consequently the growth rate at time *t-1* is: $g_i(t-1) = s_i(t-1) - s_i(t-2)$.

We thus consider short-term growth rates. Notice that the procedure for normalizing size described previously, automatically normalizes growth rates with respect to the average industrial growth rate, as

$$\begin{aligned} s_i(t) - s_i(t-1) &= \left(\ln\left(S_i(t)\right) - \frac{1}{N_J} \sum_{j \in J} \ln\left(S_j(t)\right) \right) - \left(\ln\left(S_i(t-1)\right) - \frac{1}{N_J} \sum_{j \in J} \ln\left(S_j(t-1)\right) \right) = \\ &= \left(\ln\left(S_i(t)\right) - \ln\left(S_i(t-1)\right) \right) - \left(\frac{1}{N_J} \sum_{j \in J} \ln\left(S_j(t)\right) - \frac{1}{N_J} \sum_{j \in J} \ln\left(S_j(t-1)\right) \right) \end{aligned} \tag{4}$$

As the focus of the paper is on size, all analyses are conducted on the whole sample as well as on four different subsamples, obtained by dividing firms according to their size. The subsamples include respectively:

MICRO firms, less than 20 employees;
SMALL firms, 20-99 employees;
MEDIUM firms, 100-199 employees;
LARGE firms, more than 200 employees.

The choice to analyse four size sub-samples is to enable comparison with previous studies which usually do not include micro firms (Bottazzi et al., 2002, 2003, 2007; Coad, 2007), and generally focused mainly on medium-large firms. In general, this choice in the past has been dictated by the data availability. Since in our case data on the entire population are available, it is interesting to compare the different sub-samples in order to provide some new empirical evidence on a part of the firm population that has been neglected.

3. Methodology

In order to analyse persistence and intra-distributional mobility of firm growth rates, we apply parametric and non parametric methods. First, we verify whether growth rate distributions are stable over time, and whether there are some particularities in their shape. We perform a graphical analysis by comparing histograms of relative frequencies and conduct Cramér von Mises tests (Anderson, 1962) to check whether distributions change along time. Second, we study the autoregressive structure of growth rates by means of the following quantile regression (Koenker and Bassett, 1978):

$$g_i(t) = \alpha_\theta + \beta_\theta g_i(t-1) + u_i(t)$$

with

$$\text{Quant}\left(g_i(t) \mid g_i(t-1)\right) = \alpha_\theta + \beta_\theta g_i(t-1)$$

where α_θ and β_θ are the parameters to be estimated, u is the vector of residuals, and $\text{Quant}\left(g_i(t) \mid g_i(t-1)\right)$ denotes the θ^{th} conditional quantile of $g_i(t)$ given $g_i(t-1)$. The parameter estimation procedure, for any given conditional quantile θ between zero and one, solves the following minimization problem:

$$\min_{\alpha_\theta,\beta_\theta} \left\{ \sum_{i,t:g_i(t)\geq\alpha_\theta+\beta_\theta g_i(t-1)} \theta \left| g_i(t) - \alpha_\theta - \beta_\theta g_i(t-1) \right| + \right.$$
$$\left. + \sum_{i,t:g_i(t)<\alpha_\theta+\beta_\theta g_i(t-1)} \left(1-\theta\right) \left| g_i(t) - \alpha_\theta - \beta_\theta g_i(t-1) \right| \right\}$$

There are two reasons for this choice. On the one hand, growth rate distributions display a “tent” shape, which departs from the assumption of error normality in favour of more heavytailed distributions. On the other hand, following the intuition suggested by Coad (2007) for firm growth autocorrelation and later employed to relate firm growth to industry characteristics (Reichstein et al., 2009), we prefer not to restrict attention to the mean or the median of the conditional distribution of the dependent variable (as in OLS and Least Absolute Deviation regressions), and instead retrieve a different growth autoregression parameter β_θ for each quantile θ of the conditional distribution. In our study, the regression is computed for a pooled cross-section of firms, such that the growth rates between years *t-1* and *t* are regressed on the growth rates between years *t-2* and *t-1* for the same firms, considering all the years *t* between 1996 and 2004 simultaneously.

Third, we estimate slightly modified TPM on the deciles of the growth rate distributions to derive some descriptive statistics on firm intra-distributional mobility. The transition probability matrix **P** is the matrix with p_{kh} as the elements measuring the probability of moving from decile k to decile h in one period (Hoel et al., 1987). This probability is relatively high (low) when the corresponding value in the transition matrix is higher (lower) than 0.1. Indeed, if for any given growth rate observed at time *t-1* the probability of moving to a particular growth decile at time *t* were uniformly distributed across the ten possible target deciles, then each of the ten deciles at time *t* would have exactly 1/10 probability of including the new growth rate. We compute one-year period TPM, that is, matrices where the input set (vertical axis) considers the growth $g_i(t-1)$, and the target set (horizontal axis) considers the growth $g_i(t)$.

A final remark on methodological issues is required, namely in relation to the balancing procedure applied to the growth rate distributions. In fact, the panel is balanced for each couple of years, that is, for each year *t* we need firms to be present in year *t* and in year *t-1*. In addition, size classes are defined at year *t-1*. For example, the group of micro firms includes all firms with less than 20 employees at year *t-1*, while at time *t* they may have more than 20 employees. When we compute the growth quantile autoregressions and build the transition matrices, for each year *t* we consider the size of the firms present in the database at time *t-2*, *t-1* and *t* (excluding exits that have occurred in each three-year time span). The size classes are then defined at year *t-1* to be consistent with the subsampling procedure applied earlier when plotting the growth rate distributions. The quantile regressions and the TPM are used to explain the growth rates $g_i(t)$ of the group defined at *t-1*, and therefore, for each time *t*, the dependent variables of the quantile regressions and the target sets of the TPM must be the growth rates $g_i(t)$ of the group defined at *t-1*.

This choice is thus a consequence of the role played by the different methodologies applied in this paper. This is the reason why we introduce a modification in computing the TPM, that is, we normalize each cell probability by the column sum and not the row sum, which is normally used when estimating TPM. Therefore, the one-year transition probability is defined as:

$$p_{kh} = P(X_{t-1} = k \mid X_t = h) \tag{5}$$

where $t = 1995, \dots, 2004$.

The TPM $\boldsymbol{P}$ is the matrix with p_{kh} as elements measuring the probability of moving to state h from state k in one year. In other words, each cell in our TPM shows the probability that firms have to start from the k-th decile at time $t-1$ given they end up in the h-th decile at time t.

However, in practical terms the use of the column sum instead of the row sum exerts only a minor influence on the estimated probabilities, because the use of deciles on both the row and the column implies that, except for the first and the final years of the considered time span, the firms belonging to the same k-th decile of growth rates in a given year t will contribute in equal terms to the k-th row sum and to the k-th column sum, since they belong for year t to the target set and for year $t+1$ to the input set.

4. Growth Rate Distributions

Figure 1 represents the empirical distribution of firm growth rates for all the years included in the dataset, obtained by using the number of employees on the horizontal axis and the number of frequencies on the vertical axis, and excluding firms that exited in each two-year time span. Note that the scale of the vertical axis is logarithmic. The growth rate distributions look tent-shaped and approximately symmetric regardless of the year. The body of the distribution recalls the Laplace distribution found by Stanley et al. (1996) for firm growth rates, while the tails look slightly fatter than expected, suggesting the possibility of a more ductile fitting by an exponential power (Subbotin) distribution with a shape parameter slightly lower than 1 (see Bottazzi et al., 2002). Comparing the first and last year growth distributions (Figure 2) we can see a decrease in relative frequencies in the tails, especially in the right tail. This decrease is more evident in Figure 3, where the evolution over time of the

10th and the 90th percentiles show the shrink in the distribution towards its central part. Table 1 shows that the two-sample Cramér von Mises test statistic, computed for all the years considered in order to compare the distribution of growth rates in year *t* with the distribution of growth rates at time *t-1*, is very high and leads to a strong rejection of the hypothesis that each pair of relative frequency distributions represents the double realization of a unique data generating process. However, the decrease in the statistic over time points to a tendency for less unstable distributions in more recent years.

An important departure from what Bottazzi et al. (2002, 2007) find, is the width of the distribution, which appears to be much larger in our case. A possible explanation of this different width (or scale) might be that the firms considered by Bottazzi et al. (2002, 2007) had more than 19 employees in all the years under consideration. Therefore, the numerous changes in size in the shift from micro to small or larger firms were not observable in their dataset. If we disaggregate according to size, as shown in Figure 4, the growth distribution loses its symmetry in favour of an increase in the right tail for firms with fewer than 20 employees, and an increase of the left tail for all the other firms. The growth rate distributions of small, medium and large firms thus appear left-skewed and bimodal, with the slope of the left tail appearing much flatter than the slope of the right tail. For micro firms, on the other hand, the distribution appears left-truncated, with the slopes of the two tails looking similar. The apparent symmetry in Figure 1 is a result of the combination of the left-skewness observed for small, medium and large firms, related to episodes of poor performance experienced by larger firms, and the left-truncation observed for micro firms, related to the fact that firms cannot have less than zero employees and therefore exiting firms cause the truncation.

The negative relation between size and growth has been found in several studies (e.g. Evans, 1987, and Hall, 1987). The doubts raised by the possibility that this relation could only be due to the exclusion from the database of exiting were dismissed by Dunne and Hughes (1994) and Harhoff et al. (1998), who confirm that smaller companies grow faster even after controlling for sample attrition. The growth rate distributions in our dataset allow us clearly to distinguish between the sample attrition effect, shown by the left truncation of the distribution for micro firms, and the real economic phenomenon of a negative effect of size on growth, shown by the shrinking in the right tail as we move from micro to small, medium and large firms. In other words, the negative influence of size found by regression studies in the literature can be described in terms of the asymmetric Subbotin distribution terms used by Bottazzi and Secchi (2003), not as a negative effect of size on the location parameter (the distribution always appears centred on zero), but as a negative effect of size on the scale parameter of the right part of the distribution.

It could be argued that in a balanced panel the scale of the distribution also can be biased by the exiting firms, and therefore even the positive distributions of micro and small firms are not comparable as the frequencies of the right tail must be considered in relation not only to the overall number of frequencies in the whole "truncated tent", but also to the number of firms that exited the database. In order to show that the change in scale in the right part of the distribution is not simply an outcome of sample attrition, we rescaled the distributions with respect to the total number of firms existing at time *t-1*, including firms that not longer exist at time *t*. Whatever negative growth rate we assign to these firms, the scale of the right (i.e. the positive growth rate) part of the distribution is directly comparable across size classes. Therefore, we divide the frequencies of growth rates of micro and small firms (shown in the top panels of Figure 4) by the sum of all the firms existing in the first of each pair of years for which we computed growth rates. In other words, we divide the frequencies of the growth rates between years *t-1* and *t* for micro and small firms that survive in both years by the number of firms existing at time *t-1* including firms that exited in time *t*. The resulting relative frequencies that correspond to positive (normalized) growth rates are plotted on a log scale in Figure 5 (relative frequencies equal to zero are represented as zeros on the log scale). The plot shows that, even after controlling for the number of exit firms, extreme events of positive growth are clearly relatively much more frequent for micro firms than for larger firms, and can still be encompassed in a Laplace/Subbotin framework where the tent (on its right side) simply has a lower scale for higher average size.

5. Regression Analysis

We next turn to the quantile regressions to detect possible patterns of autocorrelation in firm growth. In particular, for the pooled cross-section of firms that existed between 1994 and 2004, obtained after balancing the panel at each three-year time span, we regress the growth rate for each firm at time *t* on the growth rate for the same firm at time *t-1*. As expected, the autoregression parameter β_θ is very close to zero at the median of the conditional distribution (i.e. for θ close to 0.5), for the whole sample as well as for the different size classes (see Figures 6 and 7). However, the subsamples shown in Figure 7 are different in terms of their behaviour at quantiles that do not correspond to the median. Given the high percentage of micro firms within our database, the whole sample and the subsample of micro firms show many similarities. In particular, the coefficient is close to zero for most quantiles, but becomes negative for the extreme quantiles. In other words, the micro-firms which at a given year experience extreme events of positive growth are on average firms that in the previous year experienced events of lower growth. For the negative case, the absolute value of the size decrease at a given year is not necessarily strong: it can also be mild, being linked on average to previous episodes of even milder negative growth. The negative relation can be detected on a larger range of quantile values when we consider firms with more than 19 and less than 100 employees (small firms). However, both the coefficient values and the width of the confidence intervals at high quantiles look larger, indicating that above-average growth at time *t* cannot be attributed completely to a rebound after poor performance at time *t-1*.

The results for micro and small firms would seem to confirm the results in the literature (see e.g. Garnsey and Heffernan, 2005) while the results for medium and large firms, depicted in the bottom panels of Figure 7, are less similar to those found in previous studies. We find there is a positive parameter for quantiles between 0.1 and 0.5 in the subsample of medium firms and for quantiles between 0.5 and 0.9 in the subsample of large firms, while the parameter remains negative for the extreme quantiles. In other words, medium firms situated in medium-high quantiles seem to benefit from previous episodes of growth, but this is not the case for extreme events. The fact that firms belonging to extremely high quantiles have a negative coefficient even when these are large firms, is robust to the non-normalization of growth rates to average sectoral growth, and defines a difference with respect to the work done by Coad (2007) and Coad and Hölzl (2009), who find a positive coefficient for large firms. However, these studies introduced firm size directly into the regression as an independent variable, while here we study a “pure” autocorrelation of growth rates and consider firm size differences only by subsampling the data into the four groups previously described. Moreover, the two above-mentioned works consider size at *t-1* where growth rates between *t-2* and *t-1* and between *t-3* and *t-2* are among the explanatory variables, which is consistent with the objective of studying the direct effect of size on growth, but which makes the interpretation of results on the autocorrelation of growth rates even more difficult.

6. Discussion of the Regression Results

In Section 5 we analysed the behaviour of firms situated in different positions in the conditional growth rate distribution at time t, i.e. conditional to growth rates at time $t-1$, and found that, when considering the whole sample, firms with very high or very low conditional growth rates at time t are characterized by a negative autoregression parameter, while this coefficient is negligible for firms that are close to the conditional median. This could be based simply on a decreasing skewness of the conditional distribution of growth rates at time t as the conditioning growth rate at time $t-1$ increases, and the median is stable. This scenario is described by the example in Figure 8 which depicts three groups of seven points, belonging to a bi-dimensional space defined by the x and y axes, that are situated respectively at a negative, zero and positive value on the x axis, but where within each group the y coordinates are different. Suppose also that the median of the groups is equal, but the highest ys in the first group are higher than the highest ys in the second and third groups, and the lowest ys in the first group are higher than the lowest ys in the second and third groups. This is tantamount to saying that the slope of the linear relation linking x and the high conditional quantiles of y (conditional to x) is negative, the slope of the linear relation linking x and the low conditional quantiles of y (conditional to x) is negative, and the slope of the linear relation linking x and the conditional median of y (conditional to x) is flat. In Figure 8, the points corresponding to the conditional first and fifth sextiles respectively (for each x we have 7 points i.e. 6 intervals) are marked by a cross and a triangle, and have been fitted by quantile regressions estimated on the whole sample of 21 points at quantiles 1/6 and 5/6. The slopes of the two lines is negative, which depends simply on the fact that the conditional distribution of y given x=-4 is right skewed, while the conditional distribution of y given x=4 is left skewed. Note that, if the tails of all the conditional (and therefore also the unconditional) distributions are sufficiently fat, the y values may be very high even if the slope of the line obtained for the fifth conditional sextile is negative. It should be noted also that, in this scenario, the median of the conditional distribution of y remains fixed, but the mean is decreasing with x.

If we interpret the 21 points as 21 firms whose growth rates at time $t-1$ are measured on the x axis and growth rates at time t are measured on the y axis, then, in presence of fat tailed growth rate distributions, a negative coefficient of the fifth conditional sextile would correspond to a subsample of firms (top-left corner of the figure) with very high growth rates at time t and negative growth rates at time $t-1$, and a subsample of firms (top-right corner of the figure) with lower but still high growth rates at time t and high growth rates at time $t-1$.

Roughly speaking, for that given conditional quantile, the slope of the quantile regression line (i.e. the autoregression parameter) is negative, but the intercept is so high that it is still possible for a firm to show persistent growth. On the other hand, on average, the growth rate at time *t* is lower for firms that experienced high growth rates at time *t-1*.

If we return to the real data, in Figure 9 (left) we compare the frequency distribution of the growth rates of firms showing high growth (the top three percentiles of all firms) in 1995 with the distribution of the growth rates of the same firms in 1996 (left). It appears that being in the right tail of the distribution in year 1995 raises the probability of not being in the central body of the distribution in 1996. Moreover, it raises also the probability of being in the left tail (compare the triangles at the left of -2 on the horizontal axis with the triangles at the right of 2). If we repeat the exercise for a two-year lag, i.e. growth rate distributions for the same firms in 1997, we obtain the scenario depicted in the right part of Figure 9, which shows an even fatter left tail of the distribution. Thus, the firms belonging to the right tail in 1995 have a relatively higher probability of showing poor performance in 1997, as if a mean-reversion process were acting on the selected firms. In other words, experiencing high growth in a given year seems to increase the probability of experiencing negative growth in subsequent years. The simplest explanation for this could be that extreme (positive) growers move into a higher size class and therefore their growth rate distribution becomes more left-skewed.

The scatter plot in Figure 10 charts normalized growth rates at time *t* against normalized growth rates at time *t-1* for all the years between 1996 and 2004. The star-shape of the scatter plot is a direct consequence of the tent shapes of the unconditional distributions of the growth rates. If we concentrate on the points that, for each interval of the horizontal axis, have respectively the highest and the lowest value on the vertical axis, i.e. the firms that belong respectively to the highest and lowest quantiles of the conditional distribution of growth rates at time *t*, we get the same pattern as described in Figure 8: the two groups of points seem to define two lines with negative slopes, and the conditional distributions seem to be more and more left-skewed as the conditioning growth rate at time *t-1* gets higher and higher. Notice that only the part of the graph that lies at the left of the vertical axis could be justified partially by the exclusion of exiting firms which makes it difficult for a firm to experience two consecutive strong negative growth rates and still remain in our database. As predicted, the negative coefficients obtained from the extreme quantile regressions do not preclude the existence of many firms in the top-right corner that are growing persistently and belong in both years to a high quantile of the unconditional growth rate distribution. Roughly speaking, the quantile regression, when run on the highest conditional quantiles, compares the highest part of the scatter plot in top-left part of the graph with the highest part of the scatter plot in the top-right part of the graph. The negative autoregression coefficient obtained in this study and in the studies by Coad (2007) and Coad and Hölzl (2009) tells us that the upper bound of the scatter plot is higher in the top-left corner than in the top-right corner, i.e. the upper bound of the scatter plot becomes lower and lower as we move from left to right of the picture. In economic terms, this means that the highest growth rates at year *t* observed among firms that had a poor performance at year *t-1* are generally higher than the highest growth rates at year t observed among firms that already showed good performance at year *t-1*. As a consequence, at year *t*, the highest growth rates within the whole population generally are achieved by firms that showed poor performance at year *t-1*, but there will be many firms that experience high growth rates (not the highest in the population, but higher than the average) in two consecutive years, i.e. there will be persistent winners. In particular, when the negative value of the autoregression parameter is not too high in absolute terms so that, roughly speaking, the upper bound of the scatter plot does not cross the horizontal axis (which applies to our data), then we can be certain that persistent winners exist. Indeed, they correspond to the points in the top-right corner of the scatter plot and clearly experience episodes of very high growth in both years compared to the total population.

From the scatter plot it is difficult to understand what happens "within the star", as most of the strong intradistributional movements over time, that is, the big spurts from an unconditional quantile at time *t-1* to a very distant quantile at time *t*, may correspond to very small changes in the absolute value of the growth rate, given the Laplace-like unconditional distribution of growth rates. Similarly, a low slope coefficient of the quantile regression for quantiles close to the median may be more meaningful in economic terms than a higher slope coefficient obtained for an extreme quantile. At the same time, the quantile regression is able to show only some of the firm heterogeneity by fitting with one line the points corresponding to a given conditional quantile, while more information on outperformers and underperformers could be retrieved by considering explicitly those points which, within that quantile, are far from the linear fit. For these reasons, we need to apply another methodology that will directly infer growth persistence between *t-1* and *t* among firms belonging to a given unconditional quantile at year *t*, and to include outlying firms in the resulting picture. Koenker and Hallock (2001) argue that a least squares estimation fit to subsets of the response variable according to its unconditional distribution is not possible because truncation of the dependent variable would lead to a sample selection problem (Heckman 1979). As well as suggesting the (conditional) quantile regression, these authors suggest the alternative of a binary response model for the probability that the response variable exceeds some pre-specified cutoff value. Given that firm heterogeneity and outperformers are the focus of this study, a unique coefficient of a probit model linking the probability of belonging to a given unconditional growth quantile at time *t* (dependent variable) to growth at time *t-1* (independent variable) might be insufficiently flexible for our purposes. Rather, for each couple of unconditional quantiles of the growth distribution at time *t-1* and time *t*, it would be useful to know the probability of a firm ending up in the first quantile at time *t* starting from the second quantile at time *t-1*. This can be achieved by means of probability transition matrices built on the growth rate distributions of time *t* and *t-1*.

7. Transition Matrices

As Table 2 illustrates, although intra-distribution mobility seems high, the values on the matrix diagonal show clear persistence in growth rates. Values higher than 0.10 occur in all columns. The diagonal values in the first two columns (0.12 and 0. 21) can be characterized as persistent fast-declining firms and the values in the last two columns (0.22 and 0.11) as persistent fast-growing firms. So we have winners and losers. However, the high values in the lower left and upper right corners confirm the idea that firms that experience extreme growth behaviour in one year are also likely to experience extreme growth behaviour in the following year but in the opposite direction, revealing a strong rebound effect. As only some of the outperformers are able to repeat their performance the next year, and the others are likely to move towards the low quantiles of the distribution, we can claim that it is not possible to generalize about any "hare and tortoise" or "snowball" effect: the only persistence over time common to the whole set of outperformers and underperformers is a higher tendency to experience extreme events (i.e. a much higher dynamics than the rest of the population).

In order to find out whether size plays a role in this growth behaviour, we replicate the analysis at a more disaggregated level (see Tables 3, 4, 5 and 6 respectively) for each firm size group. For micro firms (Table 3), the results are similar to those obtained for the whole sample, except for a slightly higher "rebound" effect signalled by very high values at the bottom-left and top-right corners. Compared to non-micro firms, the rebound effect is highest for micro-firms. At the same time, persistent Schumpeterian winners and losers are much more pronounced for micro-firms than non-micro firms based on the high diagonal values in the first two and last two columns in the table. This result is in line with the notion of a

Schumpeterian Mark I, or entrepreneurial regime versus a Schumpeter Mark II, or routinized regimes scenario (Winter 1984; Malerba and Orsenigo 1996; Breschi et al. 2000). In the first regime, innovation is driven by the entry of micro firms operating in a technologically uncertain environment. Some firms catch on to a promising innovation path, while other firms bet on a technological dead-end. Consequently, one would expect more 'Schumpeterian' winners and losers expressed by the persistence of extreme growth events. In the second regime, innovation stems primarily from large firms operating in a technologically more stable environment, with less heterogeneous innovation rates among firms, spread across more products and over longer time horizons. This regime is consistent with less persistence in extreme growth events.

For small firms (Table 4), we still find higher than expected values on the main diagonal, but this persistence is much lower than for micro-firms, and the top-left cell contains a value that is lower than 0.1, i.e. it is difficult for small firms to experience two consecutive strong size decreases. Instead, the 0.16 probability in the bottom-left cell reveals that relatively many small firms experience a strong rebound effect from extreme positive growth at time *t-1* to extreme negative growth at time *t*.

For medium firms (Table 5), the size decrease cannot be linked precisely to a particular autocorrelation pattern, as the left part of the table shows high values around the main diagonal and in the bottom-left corner. This result was signalled by the quantile regression results in the bottom-left panel of Figure 7, where the very large confidence interval prevented the identification of a clear pattern of autocorrelation for medium sized firms. However, the high values in the first and last cells in the first column in Table 5 add new information: medium firms that experience very bad performance at time *t* are likely to have emerged from another extreme event, positive for some and negative for others, at time *t-1*.

Finally, for large firms (Table 6), it should be noted that the last column in the matrix shows the highest growth decile at time *t*. This is a signal that large firms have a particularly high probability of coming from the two highest-growth deciles (0.14 and 0.12) and the lowest-growth decile (0.13) at time *t-1*. On the other hand, firms showing relatively bad performance at time *t* seem to be those that experienced episodes of high growth (high values in the bottom-left part of the table) rather than low growth (low values in the top-left part of the table). As shown by the quantile regressions, growth persistence is still important in the central part of the distribution (high values in the central part of the main diagonal in Table 6).

8. Acquisitions and Spin-offs

The above analysis examines patterns of growth, but does not distinguish between different modes of growth. In this section we concentrate on acquisitions and/or spin-offs as sources of external growth as opposed to internal growth. While still pooling in a unique cross-section all the growth rates observed at each year between 1995 and 2004, we now distinguish among firms that were involved in acquisitions and firms from which other firms were spun off in the corresponding period.

We can define "*mutations*" acquisitions and spin-off events, and "*mutated firms*", firms that during time *t* experienced acquisitions and/or spin-offs, since firm size is proxied by the number of employees at the *end* of each period,

In the same figure we plot the growth rate distribution of all the firms and the growth rate distribution of the firms who made the acquisitions, to provide the histogram in Figure 11. The left tail of the acquiring firms' distribution appears to be parallel to the left tail of the whole sample, which means that, given the log scale of the vertical axis, the proportion of firms making acquisitions remains constant for all levels of negative growth. For the right tail the picture is different: the tail of the acquiring firms appears fatter, signalling that the proportion of acquiring firms increases as the growth rate becomes higher. Figure 12 shows that the asymmetry is greater in the growth rate distributions of the firms that spun off other firms. The right tail is very steep while the left tail is very fat, signalling that only a few of the split firms experienced positive growth .

If we merge the two graphs, we obtain Figure 13, which suggests that especially in the body of the distribution there may be firms that experienced both acquisitions and spin-offs. We carried out separate analyses of the effect of acquisitions and spin-offs for each of four size classes defined in Section 2. As we move from Figure 14 to Figure 17, i.e. from micro firms to large firms, the proportion of firms that made acquisitions becomes higher and higher in the right tail of the growth rate distribution. In particular, extreme episodes of negative growth rates for medium and large firms can be ascribed only to internal factors, while positive growth in many cases is associated with acquisitions.

We then estimated the TPM on the population of firms excluding those that experienced episodes of acquisitions or spin-off during each three-year time span used to estimate the matrix (see Table 7). With the exception of the cells in the bottom-right corner, whose higher numbers mean a higher persistence of growth in the top quantiles, the TPM is very similar to that obtained from pooling internal and external growth. On the other hand, moderate growth episodes appear less persistent, while intradistributional mobility in low quantiles appears to be unchanged. In other words, extreme growth events based on external sources are not likely to be repeated over time, or at least not at the same magnitude, whereas the (relatively) extreme events that are based solely on internal growth may be persistent over time. Note also that excluding only firms that have made acquisitions (Table 8) or have spun off firms (Table 9) does not change the matrix significantly. Thus, our conclusions regarding the co-existence of bouncing firms and persistent outperformers are shown to be robust if we exclude firms involved in acquisitions or spin-offs.

9. Conclusions

Using data on the whole population of Dutch manufacturing firms for the period 1994-2004, we tested for the existence of firms which are able to sustain exceptionally good performance over time, and analysed their behaviour in the light of the stylized facts in the literature on industrial dynamics and in particular Gibrat's Law.

The data show that Dutch manufacturing firms display the typical tent-shaped growth rate distribution observed by Stanley et al. (1996). However, plotting the distributions for four different size groups shows that for large firms extreme events are mainly negative: extreme positive growth is rare. This may be due to the fact that although large firms may be able to exploit more business opportunities than smaller firms, they cannot overcome the barrier of market size. We can see also that the location of the distribution appears stable across different size subsamples, with the growth median always close to zero. Thus, firm size seems to have an effect only on the skewness in the growth distribution, which is lower for larger firms.

This leads to a different interpretation of the quantile regression results in the literature which are partially confirmed by our data. The quantile autoregressions of firm growth rates show that extreme growth events are likely to be correlated negatively over time, although the negative autocorrelation is weaker for large firms. It may be difficult for firms over time to repeat very good or very bad performance as some sort of rebound effect tends to occur after an extreme event. A technical explanation for this may be that extreme growth events cause important changes in firm size, and a positive extreme growth event for a small firm (less likely for a large firm) results in a medium-large size firm and thus a lower probability of another strong growth event. The same explanation holds for large firms experiencing high negative growth, which reduces their size and makes them more likely to experience an episode of positive growth.

The estimated TPM, however, showed that, even if a bouncing back from an extreme growth event is the rule for most firms, there are still firms that are able to repeat their good performance over time. On the one hand, this result confirms that very dynamic firms are usually very different from other firms in that they can show strong autocorrelation patterns (Coad, 2007), and on the other hand, within the sample of very dynamic firms we can see that there are two, coexisting, well-defined subsets, a bigger one showing high negative autocorrelation and a smaller one showing high positive autocorrelation. If a firm, at a given year, experiences an extreme growth event, it is safe to say that the same firm is unlikely to be stable in the following year and can be expected to experience another extreme event; however, it is not possible *a priori* to predict the direction of such an event. Many of today's extreme growers will decrease in size tomorrow, but some will maintain positive extreme growth, while a few will stabilize at the newly achieved size. In other words, bouncing firms co-exist with persistent outperformers. This phenomenon shows up more clearly in the case of micro firms, thus providing support for the notion of an entrepreneurial regime as opposed to a routinized regime. It is also robust to the exclusion, from the analysis, of external growth, since we repeated the exercise after excluding firms that experienced episodes of acquisition or spin-off.

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Figure 1: Growth rates distribution, 1995-2004

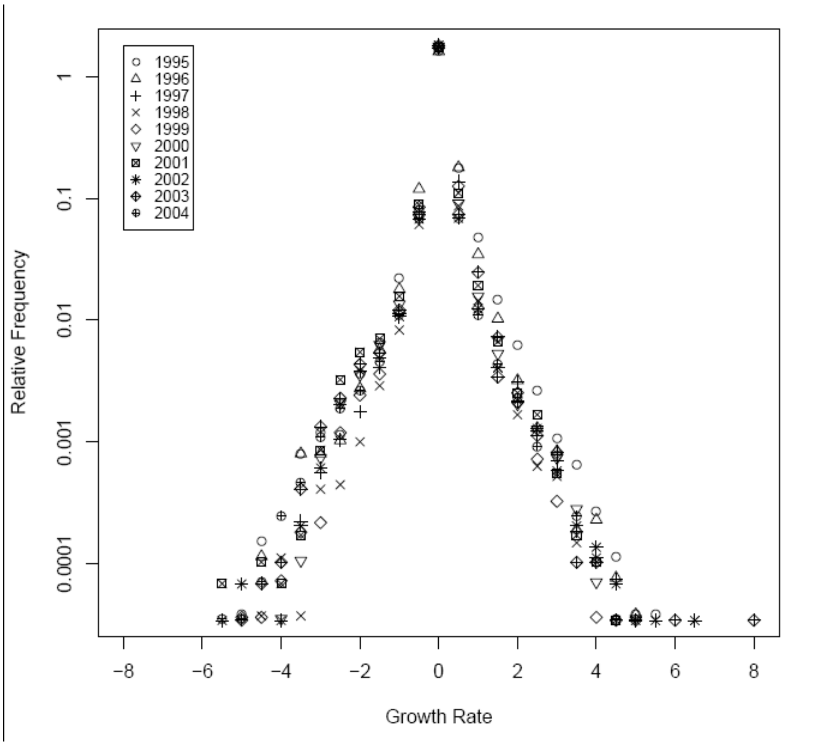

Figure 2: Growth rates distribution for the years 1995 and 2004

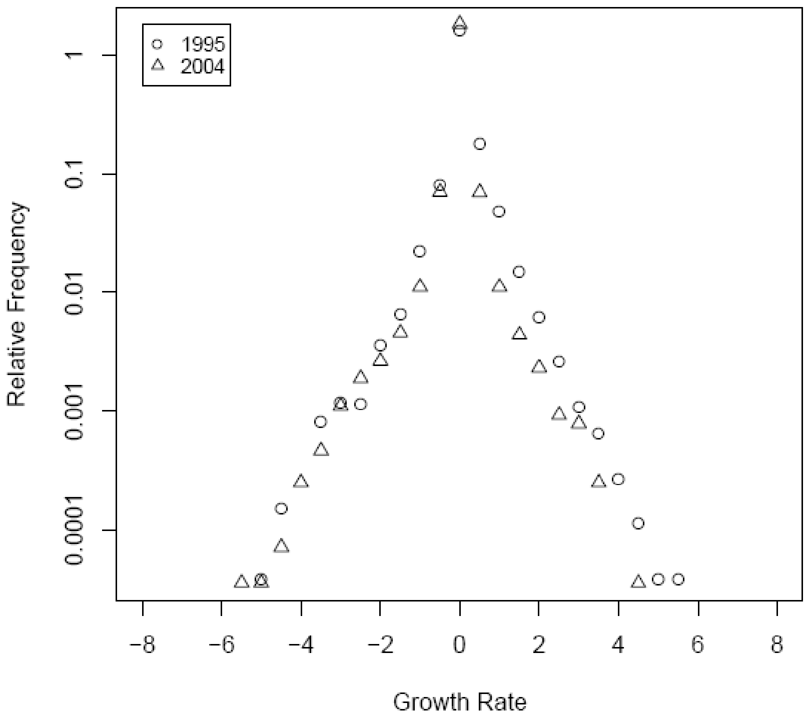

Figure 3: Evolution over time of median, 10th percentile and 90th percentile of the growth rate distribution

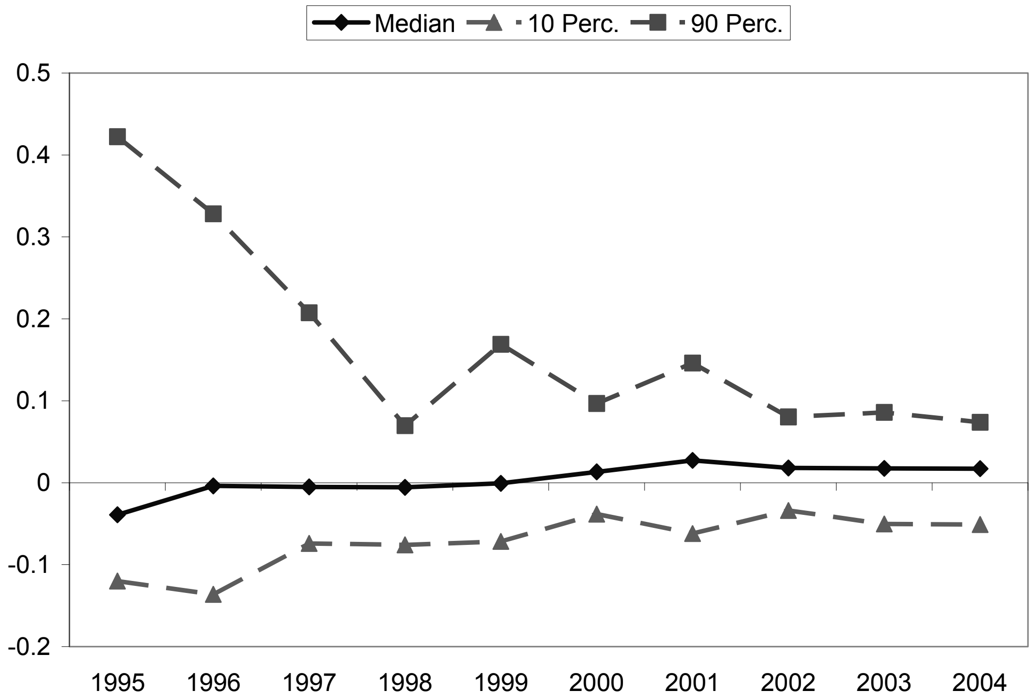

Figure 4: Growth rates distribution, 1995-2004:
micro firms (top left); small firms(top right);
medium firms (bottom left); large firms (bottom right)

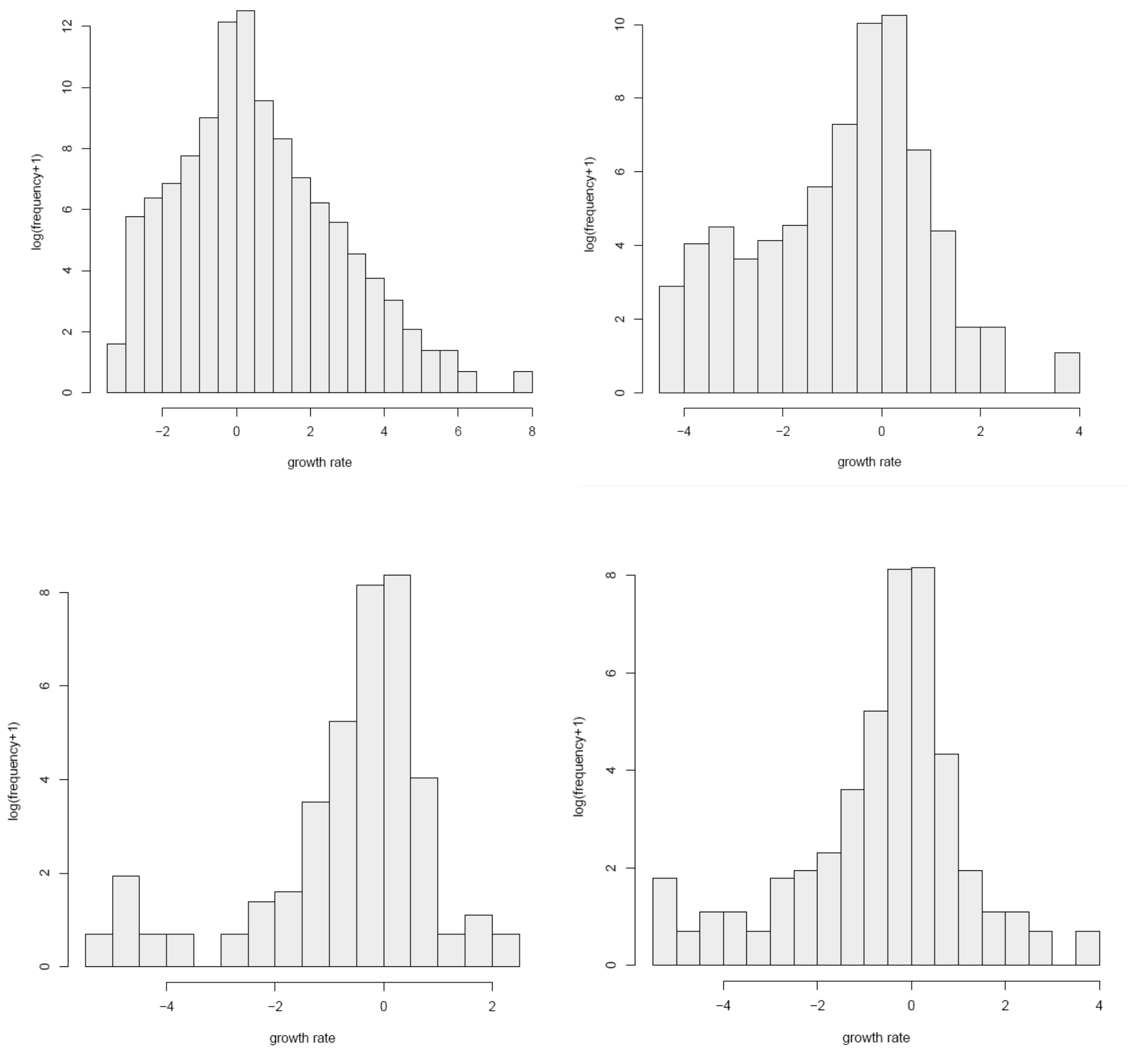

Figure 5: Density plot of normalized growth rates, 1995-2004:
Zoom on the right (positive) part of the distribution;
frequencies expressed in relation to the overall initial sample size (including exits);
zeros in the plot represent zero density.

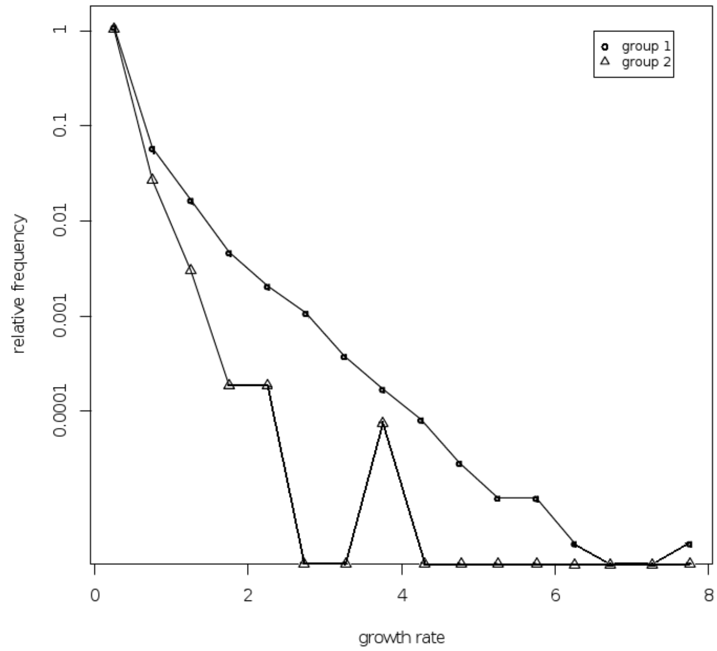

Figure 6: Quantile autoregression of growth - whole sample

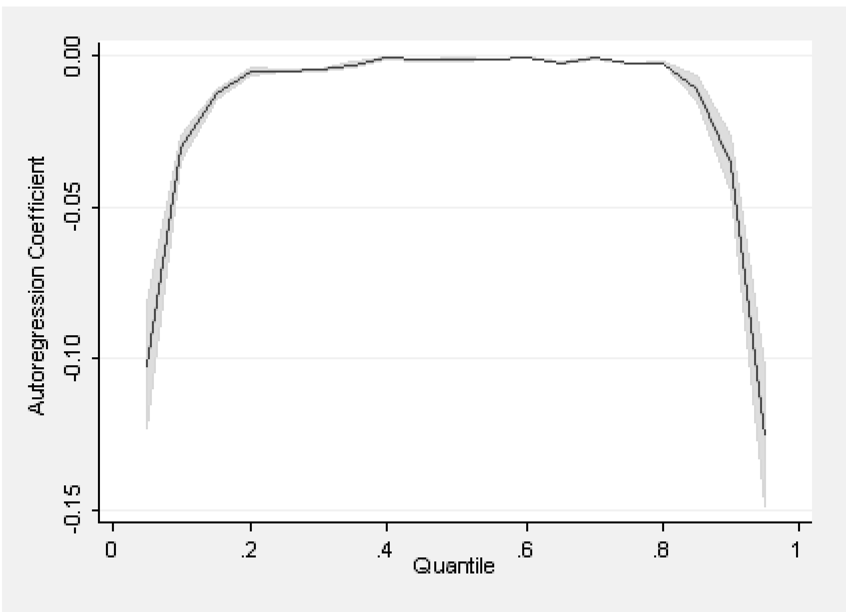

Figure 7: Quantile autoregression of growth –
micro firms (top left); small firms (top right);
medium firms (bottom left); large firms (bottom right)

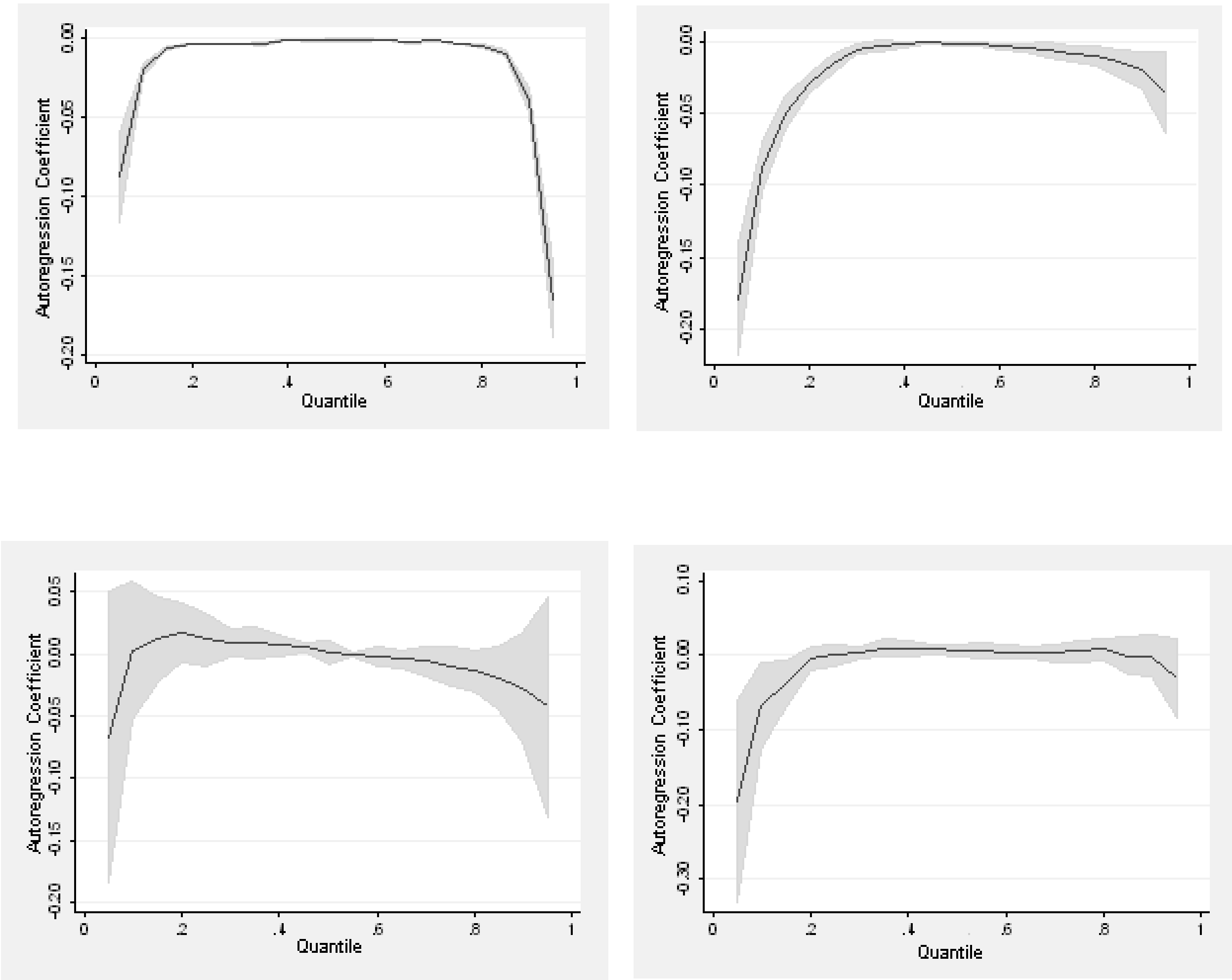

Figure 8: Theoretical example of negative slope on extreme conditional quantiles and zero slope on the conditional median

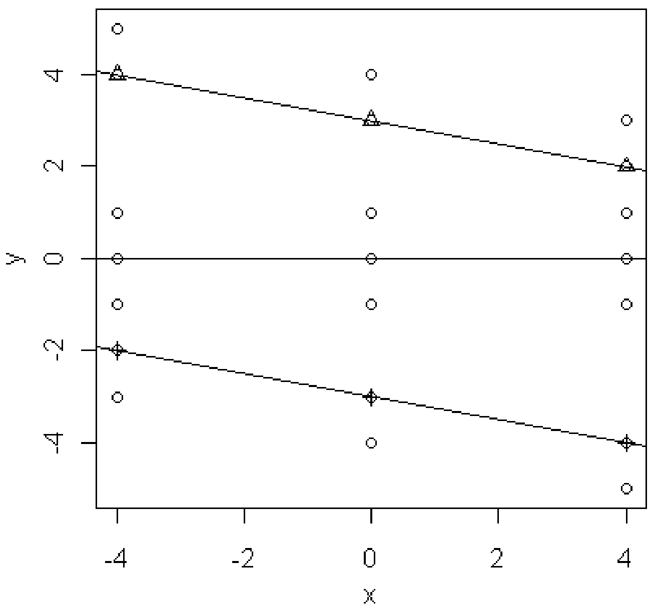

Figure 9: Growth rates distribution for the years 1996 (left panel, triangles) and 1997 (right panel, triangles) of the fastest growing firms (top three growth percentiles) of year 1995, as compared to their distribution in 1995 (left and right panels, circles)

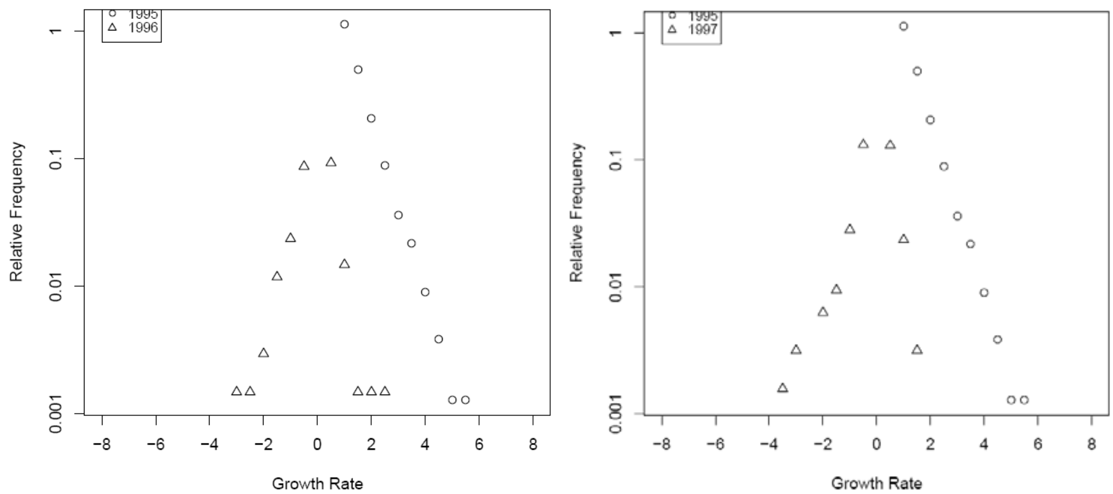

Figure 10: Scatter plot of growth rates at time *t* against growth rates at time *t-1* , 1995-2004

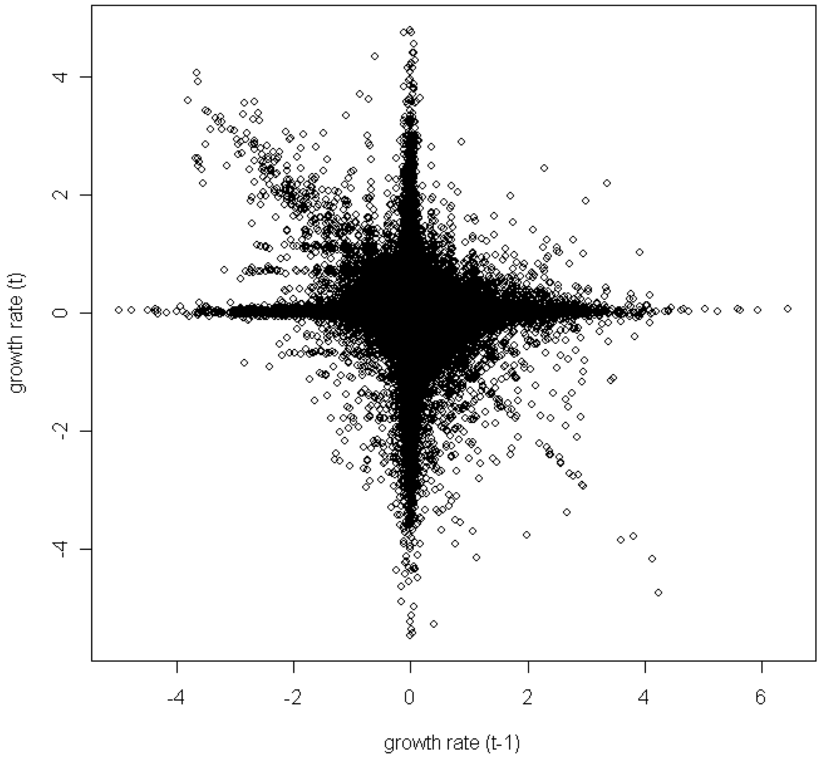

Figure 11: Growth rates distribution ,1995-2004: all firms (light colour) vs. firms making acquisitions (dark colour)

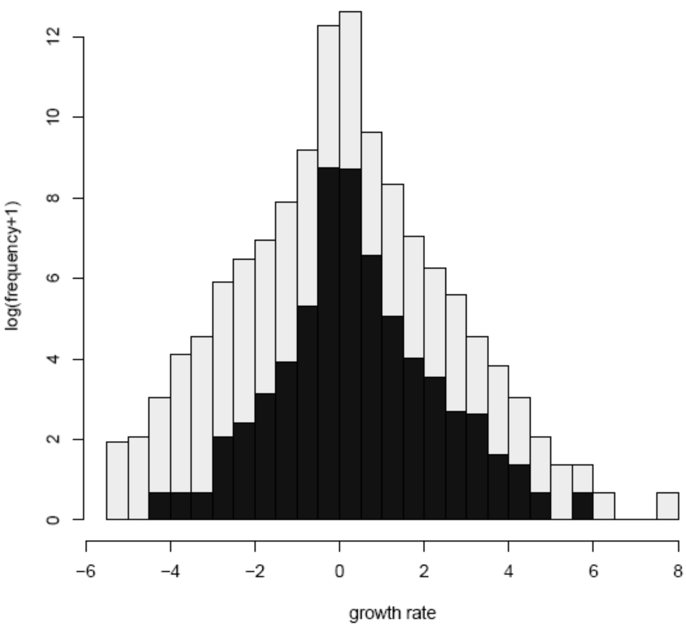

Figure 12: Growth rates distribution ,1995-2004:
all firms (light colour) vs. firms in the process of spin-off (dark colour)

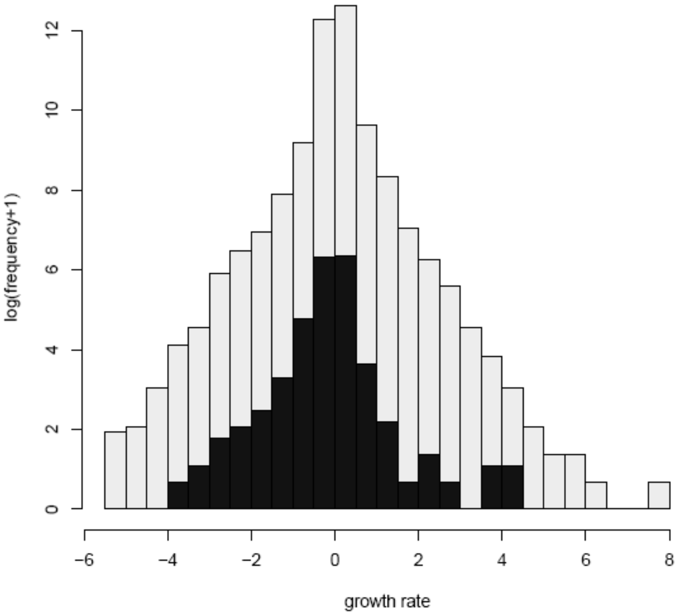

Figure 13: Growth rates distribution ,1995-2004:
all firms (light colour) vs. firms making acquisitions or in the process of spin-off (dark colour)

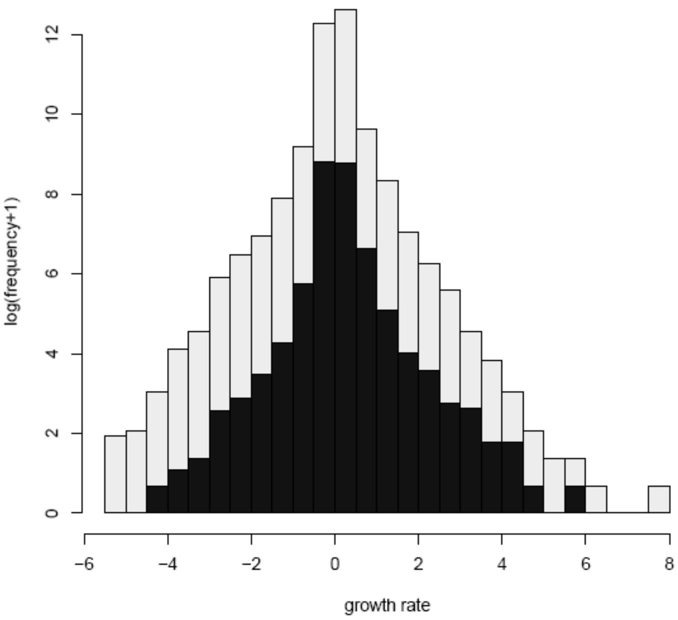

Figure 14: Growth rates distribution ,1995-2004:
all micro firms (light colour) vs. micro firms making acquisitions (dark colour)

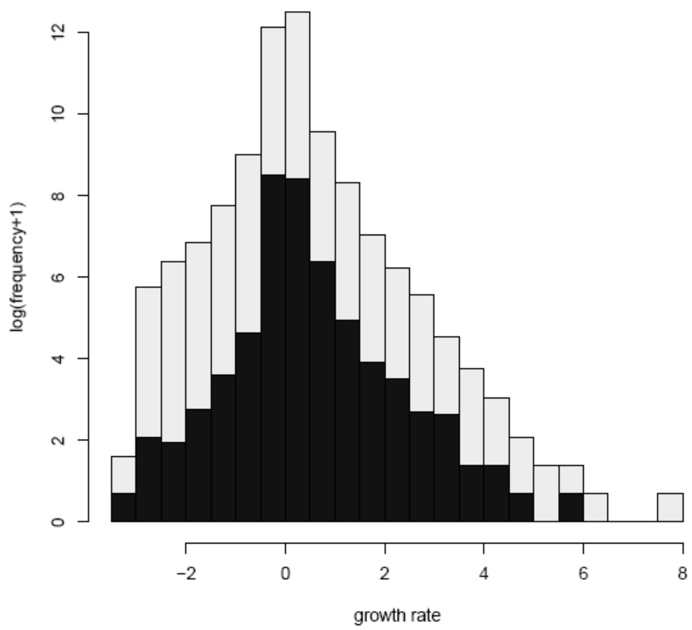

Figure 15: Growth rates distribution ,1995-2004:
all small firms (light colour) vs. small firms making acquisitions (dark colour)

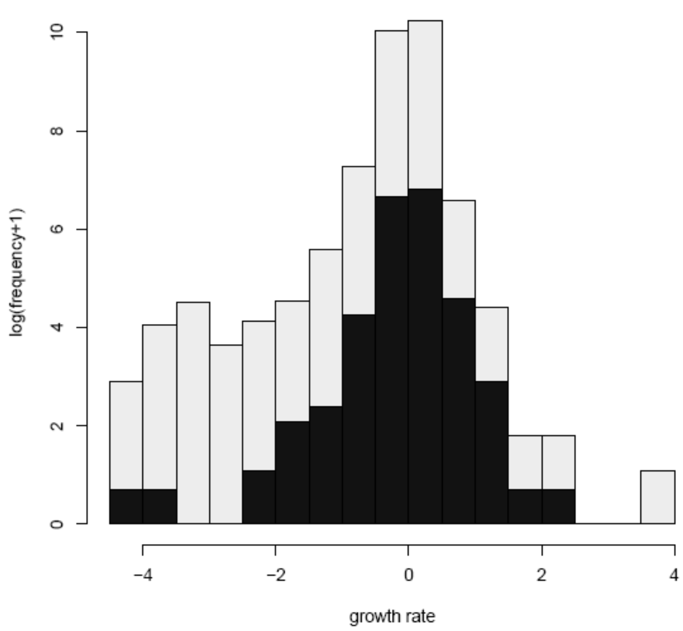

Figure 16: Growth rates distribution,1995-2004:
all medium firms (light colour) vs. medium firms making acquisitions (dark colour)

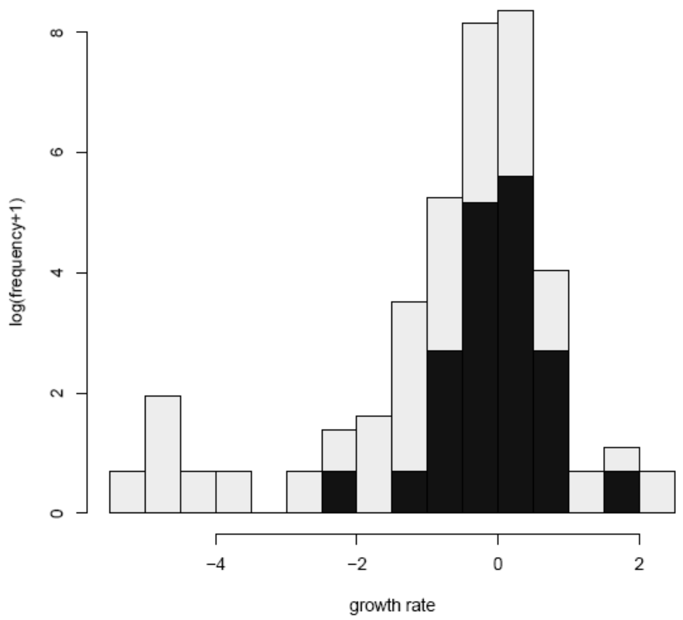

Figure 17: Growth rates distribution ,1995-2004:
all large firms (light colour) vs. large firms making acquisitions (dark colour)

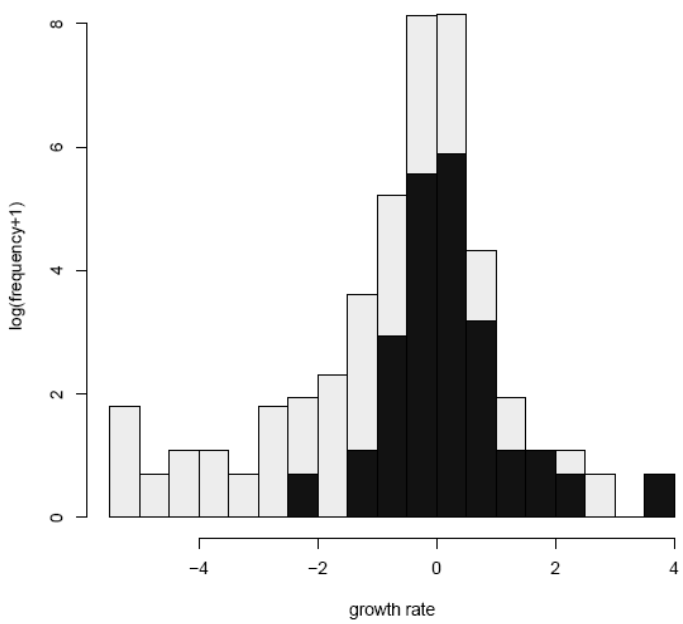

Table 1: Cramér von Mises statistic for comparing the growth rate distribution in year *t* with the growth rate distribution in year *t-1*

Year *t*	**Value**
1996	1175.081
1997	52.54619
1998	94.13955
1999	62.71444
2000	762.5912
2001	959.2009
2002	614.7111
2003	186.7675
2004	101.5324

Table 2: One-year probability transition matrix of growth rates: all sizes

Decile in year *t*	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Decile in year *t-1*										
1	0.12	0.13	0.09	0.08	0.08	0.07	0.08	0.08	0.14	0.15
2	0.09	0.21	0.11	0.06	0.10	0.05	0.09	0.06	0.11	0.12
3	0.08	0.10	0.20	0.15	0.11	0.07	0.12	0.05	0.03	0.09
4	0.08	0.08	0.19	0.23	0.07	0.11	0.03	0.06	0.07	0.08
5	0.08	0.08	0.08	0.10	0.13	0.15	0.08	0.17	0.04	0.09
6	0.07	0.04	0.07	0.11	0.19	0.17	0.08	0.14	0.06	0.08
7	0.08	0.10	0.04	0.08	0.07	0.11	0.20	0.17	0.08	0.08
8	0.09	0.06	0.08	0.07	0.08	0.15	0.16	0.12	0.10	0.09
9	0.15	0.11	0.06	0.03	0.08	0.05	0.09	0.08	0.22	0.12
10	0.16	0.11	0.08	0.08	0.08	0.08	0.08	0.08	0.13	0.11

Table 3: Probability transition matrix of growth rates: micro firms

Decile in year *t*	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Decile in year *t-1*										
1	0.12	0.11	0.10	0.08	0.07	0.06	0.08	0.07	0.13	0.17
2	0.12	0.24	0.07	0.07	0.11	0.05	0.05	0.10	0.07	0.12
3	0.08	0.08	0.24	0.15	0.11	0.07	0.10	0.07	0.02	0.08
4	0.07	0.11	0.18	0.20	0.07	0.11	0.04	0.03	0.11	0.08
5	0.08	0.08	0.08	0.10	0.13	0.17	0.08	0.15	0.05	0.09
6	0.06	0.05	0.10	0.12	0.15	0.17	0.09	0.13	0.07	0.08
7	0.07	0.10	0.02	0.08	0.11	0.11	0.16	0.19	0.08	0.07
8	0.09	0.05	0.06	0.10	0.09	0.15	0.17	0.08	0.13	0.08
9	0.14	0.08	0.05	0.02	0.08	0.04	0.16	0.09	0.20	0.13
10	0.16	0.10	0.08	0.09	0.08	0.08	0.08	0.08	0.14	0.11

Table 4: Probability transition matrix of growth rates: small firms

Decile in year t	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Decile in year t-1										
1	0.08	0.09	0.09	0.09	0.10	0.09	0.11	0.11	0.10	0.13
2	0.08	0.11	0.12	0.09	0.11	0.09	0.09	0.10	0.11	0.10
3	0.09	0.08	0.11	0.13	0.11	0.10	0.08	0.10	0.11	0.10
4	0.10	0.09	0.09	0.12	0.16	0.08	0.11	0.07	0.09	0.10
5	0.11	0.09	0.09	0.10	0.11	0.14	0.10	0.08	0.08	0.10
6	0.09	0.10	0.10	0.08	0.09	0.11	0.13	0.10	0.10	0.09
7	0.10	0.10	0.10	0.10	0.07	0.12	0.11	0.12	0.11	0.09
8	0.08	0.11	0.11	0.10	0.08	0.09	0.10	0.13	0.10	0.09
9	0.11	0.13	0.11	0.09	0.08	0.09	0.08	0.11	0.11	0.10
10	0.16	0.09	0.08	0.10	0.10	0.09	0.09	0.09	0.10	0.10

Table 5: Probability transition matrix of growth rates: medium firms

Decile in year t / Decile in year t-1	1	2	3	4	5	6	7	8	9	10
1	0.12	0.10	0.10	0.09	0.10	0.08	0.10	0.11	0.09	0.12
2	0.09	0.13	0.09	0.11	0.12	0.08	0.08	0.10	0.09	0.10
3	0.10	0.10	0.08	0.13	0.13	0.09	0.08	0.09	0.10	0.11
4	0.10	0.12	0.09	0.11	0.11	0.12	0.09	0.08	0.08	0.10
5	0.11	0.08	0.11	0.11	0.10	0.13	0.12	0.08	0.07	0.10
6	0.09	0.09	0.12	0.09	0.09	0.12	0.12	0.10	0.10	0.09
7	0.09	0.11	0.09	0.09	0.08	0.12	0.11	0.11	0.11	0.08
8	0.09	0.11	0.11	0.08	0.09	0.09	0.10	0.11	0.13	0.10
9	0.08	0.10	0.12	0.10	0.07	0.07	0.10	0.12	0.13	0.11
10	0.12	0.08	0.09	0.09	0.11	0.11	0.10	0.10	0.11	0.08

Table 6: Probability transition matrix of growth rates: large firms

Decile in year t / Decile in year t-1	1	2	3	4	5	6	7	8	9	10
1	0.09	0.11	0.09	0.11	0.07	0.11	0.10	0.08	0.10	0.13
2	0.08	0.11	0.09	0.11	0.15	0.07	0.10	0.11	0.10	0.09
3	0.08	0.09	0.10	0.09	0.13	0.08	0.11	0.11	0.11	0.09
4	0.08	0.07	0.10	0.17	0.11	0.10	0.09	0.11	0.09	0.08
5	0.09	0.10	0.10	0.12	0.12	0.12	0.10	0.08	0.08	0.07
6	0.12	0.10	0.09	0.08	0.10	0.14	0.11	0.09	0.08	0.08
7	0.11	0.09	0.10	0.07	0.09	0.13	0.09	0.13	0.09	0.10
8	0.09	0.10	0.14	0.08	0.08	0.07	0.10	0.11	0.13	0.10
9	0.12	0.11	0.10	0.07	0.07	0.08	0.10	0.10	0.11	0.14
10	0.13	0.11	0.09	0.09	0.08	0.08	0.11	0.08	0.11	0.12

Table 7: Probability transition matrix of growth rates:
whole sample, excluding firms that have been subject of acquisitions or spin-off episodes

Decile in year t	1	2	3	4	5	6	7	8	9	10
Decile in year t-1										
1	0.12	0.12	0.09	0.08	0.08	0.07	0.08	0.08	0.14	0.15
2	0.09	0.21	0.11	0.07	0.10	0.04	0.08	0.07	0.10	0.12
3	0.08	0.09	0.21	0.16	0.11	0.08	0.09	0.06	0.03	0.09
4	0.08	0.09	0.17	0.24	0.07	0.12	0.04	0.06	0.08	0.08
5	0.08	0.08	0.09	0.09	0.13	0.16	0.08	0.17	0.04	0.08
6	0.07	0.04	0.08	0.09	0.20	0.17	0.08	0.14	0.06	0.07
7	0.08	0.10	0.04	0.08	0.08	0.11	0.19	0.17	0.08	0.08
8	0.09	0.06	0.08	0.08	0.09	0.14	0.17	0.10	0.11	0.08
9	0.15	0.10	0.06	0.03	0.07	0.04	0.11	0.07	0.23	0.13
10	0.16	0.10	0.08	0.08	0.08	0.08	0.08	0.08	0.13	0.12

Table 8: Probability transition matrix of growth rates:
whole sample, excluding firms that have operated acquisitions

Decile in year t	1	2	3	4	5	6	7	8	9	10
Decile in year t-1										
1	0.12	0.12	0.09	0.08	0.08	0.07	0.08	0.08	0.14	0.15
2	0.09	0.21	0.12	0.06	0.10	0.04	0.08	0.07	0.10	0.12
3	0.08	0.10	0.20	0.16	0.11	0.08	0.09	0.06	0.03	0.09
4	0.08	0.08	0.17	0.24	0.06	0.12	0.04	0.06	0.08	0.08
5	0.08	0.09	0.08	0.09	0.12	0.16	0.08	0.17	0.04	0.08
6	0.07	0.04	0.08	0.09	0.20	0.17	0.08	0.14	0.06	0.07
7	0.08	0.10	0.04	0.08	0.08	0.11	0.19	0.17	0.08	0.08
8	0.09	0.06	0.08	0.08	0.09	0.14	0.17	0.10	0.11	0.08
9	0.15	0.10	0.06	0.03	0.07	0.04	0.11	0.07	0.23	0.13
10	0.16	0.10	0.08	0.08	0.08	0.08	0.08	0.08	0.13	0.12

Table 9: Probability transition matrix of growth rates:
whole sample, excluding firms that have been subject to spin-off

Decile in year *t*	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Decile in year *t-1*										
1	0.12	0.13	0.09	0.08	0.08	0.07	0.08	0.08	0.14	0.15
2	0.09	0.21	0.11	0.06	0.10	0.05	0.08	0.06	0.11	0.12
3	0.08	0.09	0.20	0.15	0.11	0.07	0.12	0.05	0.03	0.09
4	0.08	0.08	0.19	0.23	0.07	0.11	0.03	0.06	0.07	0.08
5	0.08	0.08	0.08	0.10	0.13	0.15	0.08	0.17	0.05	0.09
6	0.07	0.04	0.07	0.11	0.19	0.17	0.08	0.13	0.06	0.08
7	0.07	0.10	0.04	0.08	0.07	0.11	0.20	0.17	0.08	0.08
8	0.09	0.06	0.08	0.07	0.09	0.15	0.15	0.12	0.10	0.09
9	0.15	0.10	0.06	0.03	0.08	0.05	0.10	0.08	0.22	0.13
10	0.16	0.11	0.08	0.08	0.08	0.08	0.08	0.08	0.13	0.11