

Ratio Working Paper No. 197

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Abstract Most firms do not grow, and a small number of high-growth firms seem to create most new jobs. These firms have therefore received increasing attention among policymakers. The question is whether high-growth tends to persist? We investigate this question using data on 432,689 observations in Sweden during 1997-2008. We find that high-growth firms had declining growth rates in the previous 3-year period, and their probability of repeating high growth rates was very low. HGFs are essentially “one-hit wonders”, and it is thus doubtful whether policymakers can improve economic outcomes by targeting them.

Keywords Gazelles · High-Growth Firms · Persistence · Autocorrelation · Transition Probabilities

JEL Classifications L11 · L25

1 Introduction

Empirical studies (Birch and Medoff, 1994; Brüderl and Preisendörfer, 2000; Davidsson and Henrekson, 2002; Delmar et al, 2003; Littunen and Tohmo, 2003; Halabisky et al, 2006; Acs and Mueller, 2008; Acs, 2011) have shown that most new jobs originate from a small number of high-growth

We would like to thank Pontus Braunerhjelm, Alex Coad, Hans Lööf, Björn Falkenhall, Rick Wicks, seminar participants at KTH Royal Institute of Technology, Ratio, Tillväxtanalys, and Umeå University for valuable comments and suggestions. Ragnar Söderbergs Stiftelse is gratefully acknowledged for financial support.

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firms (henceforth HGFs). Coad et al (2011) also presented evidence that HGFs create employment opportunities for the young, immigrants, and long-term unemployed, groups that often have high unemployment rates and problems entering the labor market.

HGFs might thus be important for policy, and have therefore received increasing attention among policymakers in recent years. The Europe 2020 strategy, for example, explicitly mentions support of high-growth SMEs as a political objective (European-Commission, 2010; Hölzl, 2011). Studies have therefore investigated what characterizes these firms, and whether the share of HGFs differs across countries (Schreyer, 2000; Hoffman and Junge, 2006; Bravo-Biosca, 2010).

The purpose of this paper is to study the persistence of firm growth in Sweden during 1998-2008. We are interested in particular in whether high growth rates among Swedish firms tend to persist, i.e., did “winners” in one period have a higher probability of outperforming again in the next period? This question is important since HGFs have most often been analyzed statically. Policy implications from these studies are of little relevance if firm growth is random, i.e., if HGFs in period t in general are not HGFs in period $t + 1$. The relevance of studying HGFs at a specific point in time depends on whether high growth rates tend to persist.

The early literature on persistence suggests that firm growth is characterized by positive autocorrelation (Ijiri and Simon, 1967; Singh and Whittington, 1975), but results from recent studies have been more ambiguous. Some have found that firm growth is characterized by positive autocorrelation rates (Dunne and Hughes, 1994), whereas others have found the opposite (Goddard et al, 2002b). One problem, however, is that these studies focused on average firms; which typically experienced only marginal growth or none at all (Bottazzi et al, 2011).

Coad (2007), Coad and Hölzl (2009), and Capasso et al (2009) used quantile regression techniques to analyze whether

persistence was affected by firm size and firm growth. They found negative autocorrelation in the annual growth of small fast growing firms, making sustained growth very unlikely. Larger firms, on the other hand, showed positive autocorrelation or none. However, using transition probability matrices, Capasso et al (2009) found that some micro firms did in fact outperform repeatedly; even though the top percentile of micro firms showed negative autocorrelation. In these studies fast growing firms are defined as the fastest 10%. Thus, these studies did not really address the growth persistence of HGFs, since the 10% fastest growing firms often include slow-growing firms (Bjuggren et al, 2010).

Hölzl (2011) is the only study (as far as we know) that explicitly investigated growth persistence of HGFs using the Eurostat-OECD definition of HGFs, finding that growth of HGFs was not persistent. In the Eurostat-OECD definition, a firm is defined as a HGF if it has at least ten employees in the first year and an annualized employment growth rate over 20% during a 3-year period (Eurostat-OECD, 2007). However, this definition excludes almost all firms and a large share of jobs created. For example, it excluded about 95% of all surviving firms and 40% of all new jobs in Sweden during 2005-2008 (Daunfeldt et al, 2012).

Following previous studies (Henrekson and Johansson, 2010), we instead define HGFs as the 1% of fastest growing firms during a 3-year period, and find that rapidly growing firms are likely to show declining growth in the next period. The probability that high-growth firms will repeat high growth is as low as 0.01, which is the same probability that some arbitrary firm would be included in this growth category to begin with. This confirms Hölzl (2011)'s finding that HGFs essentially are "one-hit wonders". Our results thus question whether policymakers can create successful economic policy by targeting high growth firms.

The next section reviews earlier literature on the persistence of firm growth, while Section 3 presents the data and descriptive statistics. Section 4 describes our model analyzing firm dynamics during the study period (1998-2008), focusing on whether a firm in a particular growth category in one period is in the same or another growth category during the next period. Section 5 presents our results, while Section 6 summarizes and draws conclusions.

2 Literature on firm growth persistence

One strand of literature on the persistence of firm growth deals with Gibrat's Law of Proportionate Effect (LPE), i.e., independence between firm size and growth. Following Chesher (1979) and Tschoegl (1983), the LPE requires that growth rates be i.i.d. and random. Thus, firm growth cannot be persistent and cannot have any autocorrelation structure. Persistence in growth rates would then be sufficient to reject the law, so persistence is often not examined in its own right but

rather as a way of testing the LPE. Even though this literature considers autocorrelation indirectly and sometimes more as a vexation, the results are useful for uncovering the function it plays in firm growth.

Industrial organization literature has focused extensively on the LPE and the relationship between firm size and firm growth, dating back to Gibrat (1931), but there have been relatively few studies on the dynamics of growth rates (Sutton, 1997; Geroski, 2002; Lotti et al, 2003; Audretsch et al, 2004 provide authoritative surveys of the LPE). Empirical studies that have investigate whether firm growth rates were correlated over time are summarized in date order in Table 1.

[Table 1 about here]

The earliest studies found that the process of firm growth was characterized by positive autocorrelation. Ijiri and Simon (1967), when analyzing 90 of the largest firm in the United States, found that growth rates (taken over consecutive 4-year periods) were characterized by strong positive autocorrelation in the range of 30%. Singh and Whittington (1975) confirmed Ijiri and Simon (1967)'s finding of positive autocorrelation for comparable firms in the United Kingdom, although they found the effect to be much smaller. Both Chesher (1979) and Kumar (1985) found similar results studying UK firms in the services and manufacturing industries. The Chesher paper was seminal as it elaborated on Ijiri and Simon (1967)'s attempt to tie autocorrelation to the error term in the Gibrat process of proportional growth. It also explicated the now well-know fact that least squares estimates of dynamic regressions lead to biased estimates if the error terms are autocorrelated.

These studies each covered a small number of large firms in the service and manufacturing industries in the UK and USA during 1948-1976, so some uniformity in results is understandable. Wagner (1992), Geroski et al (1997), Weiss (1998), and Bottazzi (2002) also found evidence of growth persistence. However, Bottazzi et al (2002; 2011) found negative autocorrelation in total sales for Italian and French manufacturing firms, while Oliveira and Fortunato (2006) found that autocorrelation among Portuguese manufacturing firms was negative and around -10%. Comparing OLS with an in-between estimator (GMM), and also using the Breitung-Meyer Panel unit-root test, Goddard et al (2002b) also found about -30% autocorrelation for Japanese manufacturing firms.

Most of this literature on growth autocorrelation concerned manufacturing firms. Service firms have only recently been studied in detail (Coad and Hölzl, 2009; Oliveira and Fortunato, 2008; Teruel-Carrizosa, 2006; Goddard et al, 2004; Vander Venet, 2001; Tschoegl, 1983), and the results have also been mixed. Generally, it seems harder to detect any autocorrelation, but where found it more often is negative.

Tschoegl (1983) examining 100 of the largest international banks found weak negative autocorrelation, but con-

cluded generally that there was little autocorrelation. Goddard et al (2004) also examined financial services and found negative autocorrelation among 6,840 U.S federal credit unions. Oliveira and Fortunato (2008), examining the Portuguese service industry, found no significant autocorrelation. But Teruel-Carrizosa (2006), examining the Spanish service industry, found positive autocorrelation.

A problem when interpreting these varying result is the different countries, types of firms, periods, and methods used. The early literature finding positive autocorrelation focused on large firms, but also more recent studies did so also. It could be interesting to know about other firm sizes too since these results may not be representative.

Firm growth rates have also been shown to resemble a Laplace distribution with its characteristic “tent-shape” (Stanley et al, 1996; Bottazzi and Secchi, 2003; Bottazzi et al, 2011), with most firms not growing at all, and only a few with very high growth. The average firm is thus of limited interest. Most interesting would be to discover whether persistence in growth differs for HGFs compared to other firms.

Recent studies have used estimators such as quantile regression, generally finding negative autocorrelation for small firms, but positive or none for large firms (Coad, 2007; Coad and Hölzl, 2009).¹

However, very few studies so far have investigated whether rapid firm growth tend to persist over time. Coad and Hölzl (2009), who also included micro firms in the analysis, is an exception. They found negative autocorrelation in employment growth for fast growing firms in the Austrian service sector, but insignificant results for declining firms. Fast growing micro firms showed especially strong negative autocorrelation, making sustained growth very unlikely for these firms. On the other hand, growth for small, medium, and large HGFs was positively correlated over time. Coad (2007) also found negative autocorrelation in growth for small and especially medium-sized HGFs, whereas larger firms showed none (or positive) autocorrelation. Supplementing quantile regression with transition probability matrices, Capasso et al (2009) found that some micro firms did in fact repeatedly outperform, even though the top percentile were negatively autocorrelated.

None of these studies used a formal definition of HGFs, but rather compared persistence of growth among the 10% fastest growing firms with that of those with lower growth. Hölzl (2011) is the only researcher (as far as we know) who explicitly have investigated the growth persistence of HGFs. Using data on Austrian firms, he found that growth rates for

HGFs were non-persistent, with most HGFs being “one hit wonders” (p. 30).

3 Data and descriptive statistics

3.1 Data

We use the IFDB database, constructed by the Swedish Agency for Growth Policy Analysis (Myndigheten för tillväxtpolitiska utredningar och analyser), to test the growth persistence of HGFs. Compiled from the annual survey *Företagens ekonomi* conducted by Statistics Sweden (SCB), the data include many business-related variables, including organizational form, profitability, number of employees, and total sales. By law (SFS; 2001:99 and 2001:100), every Swedish firm is required to submit information to SCB, which means that the coverage is close to complete. The database also includes information from annual reports submitted to the Swedish tax authorities, as well as employment statistics from the register database RAMS. Our study covers all firms active during 1997-2008.

HGFs have been identified in one of two ways (Henrekson and Johansson, 2010). As noted, most studies identified them as a certain share (often 10% or 1%) of the fastest growing firms during a particular period. HGFs have also been identified as firms growing faster than some given rate, which is what the Eurostat-OECD definition does. It identifies HGFs as firms with at least ten employees in the starting year, and an annualized employment growth exceeding 20% during a 3-year period (European-Commission, 2010). We chose not to apply this definition since, as noted, it ignores smaller high-growth firms. Daunfeldt et al (2012) showed that it excluded close to 95% of all surviving firms in Sweden during 2005-2008, and about 40% of all created private jobs.

We chose to define HGFs as the 1% of firms with fastest growth in employment over a 3-year period.² Choosing a larger sample (e.g., the 10% fastest growing firms) might include firms that grew only slightly during the period (Bjuggren et al, 2010). In our data a 10% cut-off corresponds to a minimum growth rate of 65.7%.

We use the logarithmic difference in the number of employees over a 3-year period to measure firm growth, i.e.,:

$$g_{i,t} = \ln(S_{i,t}) - \ln(S_{i,t-3}), \quad (1)$$

² We can formalize the definition by relating the set of HGFs to the probability distribution of growth rates. We define HGFs as the subset of all firms with growth rates higher than some x , which correspond to growth rates with a probability of at most $1 - \tau$. The lower bound x to high growth is thus given by $\inf\{x : F(x) \geq \tau\} = F^{-1}(\tau)$ for $\tau \in (0, 1)$, where $F(x) = P(g \leq x)$ is the cumulative distribution of growth rates g . To identify the 1% fastest growing firms we set $\tau = 0.99$, then HGFs are all firms with growth rates higher than $F^{-1}(0.99)$, which coincides with the 99th percentile.

¹ Previous studies using quantile regression have not incorporate firm-specific fixed effects nor dealt with the dynamic panel bias present in the standard Koenker and Bassett Jr (1978) estimator. Future studies could, therefore, benefit from incorporating the methods outlined in Canay (2011) and Galvao (2011).

where $g_{i,t}$ is the growth rate for firm i in year t , and $S_{i,t-3}$ is firm size measured by the number of employees at the end of the previous 3-year period. To account for average industry growth, size is normalized using the average firm size of each 3-digit industry I , so that:

$$S_{i \in I,t} = E_{i \in I,t} / \bar{E}_{i \in I,t}^G, \quad (2)$$

where $E_{i \in I,t}$ is the number of employees in firm i within industry I during year t , such that $i \in I$, and where $\bar{E}_{i \in I,t}^G = \sqrt[n]{\prod_{i=1}^n E_{i \in I,t}}$ is the geometric mean at industry level. Inserting the normalized expression into (2) gives our desired measure of firm growth:

$$g_{i \in I,t} = \ln(E_{i \in I,t} / E_{i \in I,t-3}) - \frac{1}{n} \sum_{i=1}^n \ln(E_{i \in I,t} / E_{i \in I,t-3}), \quad (3)$$

in which average industry growth has been subtracted from the firm's growth rate (Capasso et al, 2009).³ We use the number of employees as proxy for firm size not only because it is the most prevalent growth indicator used in previous studies, but also because it receives most interest from policymakers. Daunfeldt et al (2010) discuss implications of using other growth indicators to identify HGFs. We use 3-year periods to calculate growth rates since most previous studies used either 3- or 4-year periods (Henrekson and Johansson, 2010). To test whether high growth in one period is reflected in high growth in the next period, we divide our sample into three periods (1999-2002, 2002-2005 and 2005-2008).⁴

With few exceptions, total growth (i.e. the sum of organic and acquired growth) has been analyzed in previous studies due to lack of information. Our analysis is also restricted to total growth since we do not have information on mergers and acquisitions. However, since persistence of acquired growth might be higher for firms that are part of a business group than for single establishments, we also present results when only firms not part of a business group are included in the estimations.

3.2 Descriptive statistics

Descriptive statistics regarding our measure of firm growth are presented in Table 2, covering 432,689 observations during 1998-2008. Most of the firms (95%) were registered as limited-liability companies and 26% were part of a business group. Average growth for firms in business groups was higher than for others. Firms with no initial employees were excluded by the use of logarithmic growth rates.

³ The expression (3) derives from the relationship between arithmetic and geometric means: $\ln\left(\frac{\prod_{i=1}^n E_i}{n}\right)^{\frac{1}{n}} = \frac{1}{n} \sum_{i=1}^n \ln(E_i)$

⁴ In section 5, for comparison and robustness, we also present results when growth rates have been calculated annually and for different 3-year periods.

[Table 2 about here]

We use the Eurostat firm size classifications: micro firms (<10 employees), 83.7%; small firms (10-49 employees), 13.4%; medium-sized firms (50-249 employees), 2.4%; and large firms (>249 employees), 0.5%. To avoid bias towards either small or large firms, we follow Coad et al. (2009) in computing average size as

$$S_{it}^{(c)} = 0.5(E_{i,t} + E_{i,t-3}). \quad (4)$$

The average firm has a logarithmic growth rate of 4.8%. Mean logarithmic growth for micro firms (3.5%) is lower than for small and medium-sized firms (11.1%), and for large firms (12.8%).⁵

To analyze whether persistence in growth depends on past growth, we also distinguish between growth categories $g^{(c)}$ using regular partitions q_j ($j = 1, \dots, 100$) distinguishing the 1% fastest declining firms ($g_{i,t}^{(1)}$); the 2-10% fastest declining firms ($g_{i,t}^{(10)}$); those with declining growth in the percentiles 11 to 25 ($g_{i,t}^{(25)}$); those with declining growth but slower than the preceding ($g_{i,t}^{(49)}$), those with positive growth but slower than the 25% fastest growing firms ($g_{i,t}^{(74)}$); the 10-25% fastest growing firms ($g_{i,t}^{(89)}$); the 2-10% fastest growing firms ($g_{i,t}^{(99)}$); and the 1% fastest growing firms ($g_{i,t}^{(100)}$).

Firms with zero growth (45% in the first period, 46.6% in the second, and 45.5% in the third period) are included in percentiles 26-74 ($g_{i,t}^{(49)}$ and $g_{i,t}^{(74)}$), which contains 49% of all observations. The last category (4,184 firms) meets our definition of HGFs. The logarithmic growth rate dividing the last two categories, and thus the minimum rate for HGFs, was 1.637 over three years. This equals roughly an annualized growth rate of $100\% \left((\exp(1.637))^{1/3} - 1 \right) = 72.58\%$, or roughly a four-fold increase in the number of employees for the *marginal* high-growth firm over 3 years.

The distribution of firm growth follows the characteristic tent-shape (Figure 1), also found in previous studies (Stanley et al, 1996; Bottazzi and Secchi, 2003; Bottazzi et al, 2011). Most firms do not grow, while a few experience high growth (those located to the right of the vertical line in the Figure). This characteristic distribution has been found to be robust over levels of aggregation, as well as across countries and with alternative growth measures (Dosi and Nelson, 2010).

[Figure 1 about here]

Table 3 shows shares of business-group membership and firm size by growth category; 46.1% of all HGFs were in a business group, but so were 45.9% of all fastest declining firms; 66% of HGFs were micro firms, another 27% small firms, compared to 83.1% and 13.4% overall (Table 2). Almost

⁵ Logarithmic growth rates are good approximation of percentage growth rates in this range.

94% of the firms with zero or modest growth rates (those in growth category $g_{i,t}^{(49)}$) are micro firms.

[Table 3 about here]

4 Firm growth dynamics

To analyze whether the growth of HGFs persist, we count the number that survived as HGFs into the next 3-year period (Table 4a). Of 1,210 firms classified as HGFs during 1999-2002, only ten survived as HGFs during 2002-2005, and none persisted as a HGF in 2005-2008. The results are similar for the 1,250 HGFs during 2002-2005; few survived as HGFs into the next period. The table also shows similar results for the fastest 3%, 5%, and 10% of firms. High growth generally failed to persist into the next period.

Following Capasso et al (2009) and Hölzl (2011), Table 5 shows the estimated transition probabilities that a firm in a given growth category (vertical-axis) in period t will be located in that or another growth category (horizontal-axis) in period $t + 3$.

The 1% of firms with the slowest growth in period t had a very low probability (0.008) of remaining in the same category in period $t + 3$. In fact, they were most likely to be HGFs in $t + 3$ (probability of 0.109), and also had probability of 0.213 of being in the second fastest-growing category. Thus, we seem most likely to find future fast-growing firms among those with the largest current job losses.

The probability of an HGF as persisting in the next 3-year period was 0.01, the same probability that any firm would be in this category to begin with. The probability that an HGF in period t would instead be in fastest declining category in the next period was almost 6 times higher (0.059), a higher probability than that of any other initial category drastically reducing their number of employees. However, HGFs were also most likely to experience moderate employment growth ($g_{i,t+3}^{(89)}$) in the next period (0.245) and they had the lowest probability of (0.051 + 0.199) of being in the middle two categories with essentially no growth in period $t + 3$. Firms with essentially no growth originally had high probabilities (0.427 + 0.196, and 0.239 + 0.366) of remaining in the same categories during the next three year period.

[Table 4 about here]

The corresponding results by firm size category are presented in Tables 6-8. We merged the results for medium and large firms (Table 8) because of few observations in these categories. Micro firms with zero or close to zero growth rates were much more likely than larger firms to remain in that category during the next period. Micro HGFs had a slightly higher probability of growth persisting (0.011) compared to

small (0.008), and medium/large firms (0.006). The likelihood of HGFs having essentially zero growth in the next period seem independent of firm size.

For medium/large firms, the fastest declining firms originally had the highest probability of fast growth in the next period (0.161), considerably higher than for small (0.128) or micro firms (0.097), and sixteen times higher than if firms were randomly distributed into growth categories.

[Table 5-8 about here]

5 Modeling autocorrelation

To model growth persistence, we assume an underlying process for (log) firm size $s_{i,t}$ with a first order autoregressive error term $v_{i,t}$

$$s_{i,t} = \alpha_i + v_{i,t}$$

$$v_{i,t} = \beta v_{i,t-1} + \varepsilon_{i,t}$$

which can be transformed into the dynamic panel

$$s_{i,t} = (1 - \beta) \alpha_i + \beta s_{i,t-1} + \varepsilon_{i,t}, \quad (5)$$

where α_i denotes firm-specific fixed effects and β denotes the effect from lagged size. The only difference from the standard Gibrat model - in which the firm-specific fixed effects are expunged at $\beta = 1$, a condition usually embodied in Gibrat's law and synonymous with the presence of a unit root in firm size - is in the constant term. Provided no serial correlation or heteroskedasticity in $\varepsilon_{i,t}$, firm size is now independent of growth (Tschoegl, 1983). If $\beta < 1$, size regresses to the mean, with smaller firms tending to grow faster than larger ones.

We are interested in the effect of preceding growth from $\Delta s_{i,t-1}$ on current growth $\Delta s_{i,t}$. If firm size follows the process in (5) then the effect can be found by deriving the autocorrelation function (ACF) given by $\gamma(\Delta s_{i,t}, \Delta s_{i,t-1}) = \text{cov}(\Delta s_{i,t}, \Delta s_{i,t-1}) / \text{var}(\Delta s_{i,t})$, where

$$\text{cov}(\Delta s_{i,t}, \Delta s_{i,t-1}) = -(1 - \beta) \sigma^2 / (1 + \beta)$$

$$\text{var}(\Delta s_{i,t}) = 2\sigma^2 / (1 + \beta),$$

which follows from the two moment conditions $E(v_{i,t}^2) = \sigma_\varepsilon^2 / (1 - \beta^2)$ and $E(v_{i,t} v_{i,t-s}) = \beta^{|s|} \sigma_\varepsilon^2 / (1 - \beta^2)$. The ACF for consecutive growth rates then becomes,

$$\gamma(\Delta s_{i,t}, \Delta s_{i,t-1}) = -1/2(1 - \beta) \quad (6)$$

which is a function of the rate of size-regression β to the mean. For $\beta \in [0, 1)$ it follows that growth autocorrelation is negative, and for $\beta \in [-1, 0)$ positive. In the special case of Gibrat's law, when $\beta = 1$, autocorrelation is zero and firm size is a random walk. Growth persistence (positive autocorrelation) only occurs when $\beta > 1$, i.e., when growth is explosive, with firms growing faster the larger they become. This is only

conceivable temporary, which implies that persistent growth rates, when they occur, are unlikely to be long lasting.

To find the ACF our empirical strategy consists of first estimating β and then using it to compute the growth autocorrelation function of consecutive growth rates γ . Various methods have been used to estimate the Gibrat model (Table 1), but most studies used OLS, as did we, though exploiting a recently proposed estimator which is more appropriate with a dynamic panel. It is well known that standard OLS and fixed effect panel estimators give biased results. To account for firm-specific heterogeneity and correct for dynamic bias, Han and Phillips (2010) proposed using *first difference least squares* (FDLS) estimator. We therefore transformed (5) into

$$2\Delta s_{i,t} + \Delta s_{i,t-1} = \beta \Delta s_{i,t-1} + \xi_{i,t}, \quad (7)$$

with $\xi_{i,t} = 2\Delta s_{i,t} + (1 - \beta)\Delta s_{i,t-1}$. The FDLS estimator of β can then be derived by applying OLS to this equation. Although the estimator depends on T asymptotics, it is robust across sets of (n, T) where $\sqrt{nT_1}(\hat{\beta}_{FDLS} - \beta) \rightarrow N(0, \sigma_{FDLS}^2)$ for each T_1 as $n \rightarrow \infty$ (Han and Phillips, 2010).

Other ways to handle endogeneity and simultaneously deal with firm level heterogeneity usually consist of various IV techniques applied to (6), such as the Anderson and Hsiao (1982) estimator, or the difference-and-system GMM estimators of Arellano and Bond (1991) and Blundell and Bond (1998) which use lags of the endogenous variable as instruments.

But the IV-approach usually requires stationarity i.e., $\beta < 1$. When $\beta = 1$ these estimators may suffer from weak instruments uncorrelated with the endogenous variable, resulting in severe finite sample bias (Bond, 2002). The FDLS estimator, on the other hand, is well suited for such situations.

To judge the accuracy of the FDLS estimate $\hat{\beta}_{FDLS}$, we follow Bond (2002) who used the fact that the OLS estimate $\hat{\beta}_{OLS}$ and the fixed-effect within-estimate $\hat{\beta}_{FE}$ of (6) result in upward and downward bias, respectively. Thus, our criteria for using the FDLS estimator amounts to $\hat{\beta}_{FDLS} \in (\hat{\beta}_{FE}, \hat{\beta}_{OLS})$.⁶

In the final estimated regression we include dummies \mathbf{D} for each of the growth categories $g_{i,t}^{(c)}$ of $\Delta s_{i,t-1}$ as specified in Table 2, together with dummies for time variant fixed effects δ_t ,

$$2\Delta s_{i,t} + \Delta s_{i,t-1} = \gamma \mathbf{D} + \delta_t + \beta \Delta s_{i,t-1} + \Gamma \mathbf{D} \Delta s_{i,t-1} + \xi_{i,t}. \quad (8)$$

The estimate $\hat{\beta}_{FDLS}$ for HGFs is then given by evaluating the marginal effect $\partial / \partial \Delta s_{i,t-1} = \hat{\beta} + \hat{\Gamma}_{HGF}$.

⁶ For the standard OLS estimator of (6) it can be shown that the bias is inversely related to β and vanishes as $\beta \rightarrow 1$. Madsen (2010) even argues that OLS can yield superior estimates even when $\beta < 1$, provided that the variation in α_i is relatively low and that $\sigma(\alpha_i) < \sigma(\varepsilon_{i,t})$, which Hall and Mairesse (2005) argue are likely for short panels of firm data.

6 Results

We first present the results when equation (8) is estimated on the complete panel of firms, followed by results when firms are divided into size categories and by membership in a business group or not. To capture segments of the growth distribution, we include dummy variables corresponding to the categories described in Section 3. Based on the relationship in equation (6), we first estimate the size mean regression parameters $\beta + \Gamma_{q_i}$ (columns (a), Table 9 below), then the autocorrelation coefficients γ presented in (columns (b)). As a base case we use growth categories $g_{i,t}^{(49)}$ and $g_{i,t}^{(74)}$, including firms with essentially zero growth.

To evaluate robustness, we also analyze alternative consecutive 3-year periods during 1998-2007 and 1997-2006. We also include results when using annual periods during 1997-2008.

6.1 Results for all firms

Table 9 shows the FDLS estimators from equation (8) for growth rates in consecutive 3-year periods during 1999-2008.

[Table 9 about here]

Growth autocorrelation tends to be negative across growth categories (columns 1b, 2b, 3b, 4b), with the exception of the base case (not shown) where autocorrelation is positive. Negative results for both growing and declining firms indicate that they were likely to have had opposite performance in the previous period $t - 1$.

Similar to Coad and Hölzl (2009) findings, our results are asymmetric, with the most pronounced negative results for HGFs (-0.138, -0.126, -0.146, -0.149). This strongly suggests that HGFs did not experience high growth in the previous period, but rather performed poorly.⁷

Statistical significant autocorrelation, as we have for all growth categories, means that we can reject Gibrat's law that firm growth is independent of firm size. In line with previous findings, growth is explosive for firms in the base case (indicated by positive autocorrelation), but since this category mostly contains firms with essentially zero growth, the result is of little interest.

The interesting exception is for firms in growth category $g_{i,t}^{(89)}$, analyzed annually (column 4b), which tend to perform well in the preceding period. But clearly such persistence did not extend to a 3-year period, or if so, not into the next 3-year period.

⁷ One consequence with introducing dummy variables on values of the dependent variable is that the results becomes backward looking rather than forward looking. Alternatively, dummies could be used for values of the lagged dependent variable, which would then allow us to assess what happened to HGFs in the current period. To enable comparison with previous studies, e.g., the quantile regression studies, we chose not to do that.

6.2 Results for firms of different sizes

To examine how growth persistence varied across size categories, we also estimate (8) for micro, small, and medium/large firms separately. Our results (Table 10) confirm Coad (2007) that persistence seems to depend on firm size.

Micro firms had greater negative autocorrelation coefficient than larger firms, suggesting that the negative correlation over time for firm growth seem to be driven by micro firms to a large extent, supporting Coad and Hözl (2009) findings. However, this result does not hold for the HGF-category. In particular, small (-0.201) and medium/large (-0.226) HGFs had substantial greater negative autocorrelation than did micro firms (-0.077). High growth thus seems hard to repeat, but even harder for larger firms. The heterogeneous results for HGFs over size categories might reflect differences between labor-intensive micro firms and capital intensive large firms with more routinized organization. While Acs (2011) found persistent growth (positive autocorrelation) only among larger firms, we found positive growth persistence only among larger firms with modest growth (percentiles 75-89), not at higher growth rates.

[Table 10 about here]

We also examined whether growth persistence differed by business group member or not, since we know that much firm growth is non-organic (i.e., through acquisitions). We found little difference for most growth categories, the exception being $g_{i,t}^{(100)}$ (HGFs). Over half of the negative result for all firms (-0.138, Table 9, column 1b) seems to be accounted for by business group membership, since non-business group HGFs had only -0.064.

7 Conclusions

Recent studies have suggested that most firms do not grow, and that a small number of HGFs create most new jobs. HGFs also seem to offer employment to groups that traditionally have had difficulty entering the labor market. These firms have therefore received increasing attention among policymakers, who sometimes explicitly mention an increasing share of HGFs as a political objective (European-Commission, 2010).

We analyzed growth persistence in Sweden using data on all firms during 1996-2008, focusing on whether HGFs in one 3-year period had higher probability of high growth again in the next period. Previous studies have in general analyzed HGFs using static analysis. Policy implications from these studies are not relevant if firm growth in fact is random, i.e., if HGFs in period t are in general not HGFs in period $t + 3$. Thus, the importance of studying HGFs at a specific point in time depends on whether high growth tends to persist.

We found that high growth was not persistent over time.

On the contrary, firms that experienced high employment growth rates in one period were most likely to have suffered job losses in the previous period. Transition probability analysis also showed that HGFs were unlikely to repeat their high growth in coming periods. Most HGFs can thus be characterized as one-hit wonders, and policies to promote HGFs that are based on their growth in a previous periods are not likely to succeed. However, HGFs were also most likely to have moderate growth in the next period.

Firms with the greatest job losses in one period were most likely to found to become HGFs in the next period. These results emphasize the extreme dynamics that occur with respect to intra-distributional movements of firms from the left and right tails of the growth-rate distribution.

We believe that future studies should focus more on what characterizes HGFs that show persistent high growth over time. As the number of such persistent HGFs seems to be remarkably low, research could probably benefit from surveys and interview studies rather than longitudinal studies using secondary data.

Another fruitful area of research is potential HGFs. Consistent with other studies (Bottazzi et al, 2011), we found that most firms did not grow at all. Some might have high profitability and the financial strength to grow, but refrain for some reason. Employment might thus be increased if industrial policy can get this relatively large group of firms to grow, rather than focusing on the growth of a small number of already fast-growing firms.

Acknowledgements We would like to thank Pontus Braunerhjelm, Alex Coad, Hans Lööf, Björn Falkenhall, Rick Wicks, seminar participants at KTH Royal Institute of Technology, Ratio, Tillväxtanalys, and Umeå University for valuable comments and suggestions. Ragnar Söderbergs Stiftelse is gratefully acknowledged for financial support.

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Table 1 Summary of previous studies

Study	Country	# Firms ^a	Growth ind. ^b	Period	Method ^c	Results ^d	HGFs ^e
Ijiri and Simon (1967)	USA	100	Sales	1948-1960	OLS	+	No
Singh and Whittington (1975)	USA	2,000	Net assets	1948-1960	OLS	+	No
Chesher (1979)	UK	200	Capital	1960-1969	OLS	+	No
Tschoegl (1983)	Several	100	BV, AV	1969-1977	OLS	0	No
Kumar (1985)	UK	2,000	Net assets	1960-1976	OLS	+	No
Contini and Revelli (1989)	Italy	1,000	Emp	1977-1986	OLS	-	No
Boeri (1989)	Several	2.7 million	Emp	1977-1990	Desc.	-	No
Wagner (1992)	Germany	7,000	Emp	1978-1979	OLS	+	No
Dunne and Hughes (1994)	UK	2,000	Net assets	1975-1985	OLS	0	No
Geroski et al (1997)	UK	300	Sales	1976-1982	OLS, GMM	+	No
Vander Venet (2001)	Several	OECD banks	Total assets	1985-1994	OLS	0	No
Geroski (2002)	USA	11	Output	1910-1998	OLS	0	No
Goddard et al (2002a)	USA	6,800	Total assets	1991-1997	OLS	-	No
Goddard et al (2002b)	Japan	500	Total assets	1980-1996	OLS, GMM	-	No
Goddard et al (2004)	Several	600	Total assets	1992-1998	OLS, GMM	+	No
Bottazzi (2002)	Italy	thousands	Sales, Emp, VA	1989-1996	OLS	+/-	No
Bottazzi and Secchi (2003)	USA	1,000	Sales	1982-2001	OLS	+	No
Garnsey et al (2006)	UK, Ger., Nethl.	400	Sales, Emp	1990-2000	Desc.	+	No
Oliveira and Fortunato (2006)	Portugal	8,000	Emp	1990-2001	OLS, GMM	-	No
Teruel-Carrizosa (2006)	Spain	42,000	Emp	1994-2002	GMM	+	No
Coad (2007)	France	10,000	Sales, Emp	1997-2005	LAD, QR	+/-	Yes
Oliveira and Fortunato (2008)	Portugal	400	Emp	1995-2001	GMM	-	No
Capasso et al (2009)	Netherlands	N/A	Emp	1994-2004	QR, TP	+	Yes
Coad and Hözl (2009)	Austria	100,000	Emp	1975-2004	OLS, QR	+/-	Yes
De Haan et al (2009)	Several	1,500	Total assets	1997-2007	GMM	0	No
Parker et al (2010)	UK	sample	Sales	1996-2001	OLS	0	Yes
Fotopoulos and Giotopoulos (2010)	Greece	3,700	Total Assets	1995-2001	OLS	+	No
Hözl (2011)	Austria	100,000	Emp	1972-2007	Probit	0	Yes
Bottazzi et al (2011)	France	10,000	Sales	1996-2002	LAD, OLS	-	No

^a Rounded to even hundreds or thousands

^b BV=book value; AV=asset value; Emp=employment; VA=value added.

^c OLS=ordinary least square; GMM=generalized method of moments ; QR=quantile regression; Desc.=Descriptive;

LAD= least absolute deviation; TP=transition probability matrices

^d +=positive persistence in growth rates; 0=no persistence; -=negative persistence.

^e Are results reported for high-growth firms?

Table 2 Logarithmic growth rates of firms

Category of firms	Obs.	Mean	SD	Min.	Max.
All firms	432,689	0.048	0.530	-6.675	9.841
<i>Type of company</i>					
Business group	113,360	0.069	0.621	-6.512	8.489
<i>Size category</i>					
Micro firms	362,235	0.035	0.504	-4.213	4.107
Small firms	57,806	0.111	0.621	-4.913	7.474
Medium firms	10,375	0.111	0.732	-6.675	5.618
Large firms	2,273	0.128	0.849	-6.643	9.841
<i>Growth category: $g_{i,t}^{(c)}$</i>					
$g_{i,t}^{(1)} : g_{i,t} \in q_1$	3,774	-2.151	0.633	-6.675	-1.566
$g_{i,t}^{(10)} : g_{i,t} \in [q_2, q_{10}]$	37,038	-0.833	0.227	-1.565	-0.605
$g_{i,t}^{(25)} : g_{i,t} \in [q_{11}, q_{25}]$	65,493	-0.265	0.146	-0.605	-0.058
$g_{i,t}^{(49)} : g_{i,t} \in [q_{26}, q_{49}]^a$	105,405	-0.021	0.015	-0.058	0.002
$g_{i,t}^{(74)} : g_{i,t} \in [q_{50}, q_{74}]^a$	107,346	0.060	0.051	0.002	0.194
$g_{i,t}^{(89)} : g_{i,t} \in [q_{75}, q_{89}]$	66,601	0.378	0.125	0.194	0.657
$g_{i,t}^{(99)} : g_{i,t} \in [q_{90}, q_{99}]$	42,806	0.894	0.256	0.657	1.637
$g_{i,t}^{(100)} : g_{i,t} \in q_{100}$	4,181	2.211	0.615	1.637	9.841

^a These growth categories are used as base case in the regression analysis

Table 3 Descriptive statistics over growth divided after share of business group membership and firm size category

	Bus. group	Micro	Small	Medium	Large
$g_{i,t}^{(1)}$	0.459	0.721	0.227	0.043	0.009
$g_{i,t}^{(10)}$	0.220	0.927	0.006	0.011	0.002
$g_{i,t}^{(25)}$	0.349	0.743	0.210	0.038	0.008
$g_{i,t}^{(49)a}$	0.168	0.940	0.050	0.008	0.002
$g_{i,t}^{(74)a}$	0.255	0.823	0.145	0.027	0.006
$g_{i,t}^{(89)}$	0.345	0.736	0.218	0.038	0.008
$g_{i,t}^{(99)}$	0.248	0.873	0.106	0.018	0.004
$g_{i,t}^{(100)}$	0.461	0.662	0.265	0.057	0.017

^a These growth categories are used as base case in the regression analysis.

Table 4 Persistence of HGFs by initial period and growth percentile

	1999-2002	2002-2005	2005-2008		1999-2002	2002-2005	2005-2008
1999-2002	1210	10	0	1999-2002	3527	90	1
2002-2005	-	1250	12	2002-2005	-	3980	69
2005-2008	-	-	1721	2005-2008	-	-	5262
(a) 1% fastest growing				(b) 3% fastest growing			
	1999-2002	2002-2005	2005-2008		1999-2002	2002-2005	2005-2008
1999-2002	6107	210	16	1999-2002	12856	789	80
2002-2005	-	6360	318	2002-2005	-	14988	1228
2005-2008	-	-	8986	2005-2008	-	-	19143
(c) % fastest growing				(d) 10% fastest growing			

Table 5 Transition probabilities for growth by percentile during 1999-2002, 2002-2005, and 2005-2008, all firms

	$g_{i,t+3}^{(1)}$	$g_{i,t+3}^{(10)}$	$g_{i,t+3}^{(25)}$	$g_{i,t+3}^{(49)^a}$	$g_{i,t+3}^{(74)^a}$	$g_{i,t+3}^{(89)}$	$g_{i,t+3}^{(99)}$	$g_{i,t+3}^{(100)}$
$g_{i,t}^{(1)}$	0.008	0.062	0.088	0.195	0.219	0.105	0.213	0.109
$g_{i,t}^{(10)}$	0.006	0.052	0.074	0.297	0.256	0.098	0.202	0.014
$g_{i,t}^{(25)}$	0.012	0.085	0.209	0.177	0.271	0.187	0.055	0.003
$g_{i,t}^{(49)^a}$	0.004	0.070	0.107	0.427	0.196	0.116	0.077	0.003
$g_{i,t}^{(74)^a}$	0.006	0.067	0.138	0.239	0.366	0.117	0.065	0.003
$g_{i,t}^{(89)}$	0.012	0.078	0.242	0.163	0.229	0.228	0.046	0.002
$g_{i,t}^{(99)}$	0.014	0.187	0.156	0.164	0.198	0.201	0.075	0.004
$g_{i,t}^{(100)}$	0.059	0.110	0.235	0.051	0.199	0.245	0.090	0.010

^aThese growth categories are used as base case in the regression analysis

Table 8 Transition probabilities for growth by percentile during 1999-2002, 2002-2005, and 2005-2008, medium/large firms

	$g_{i,t+3}^{(1)}$	$g_{i,t+3}^{(10)}$	$g_{i,t+3}^{(25)}$	$g_{i,t+3}^{(49)^a}$	$g_{i,t+3}^{(74)^a}$	$g_{i,t+3}^{(89)}$	$g_{i,t+3}^{(99)}$	$g_{i,t+3}^{(100)}$
$g_{i,t}^{(1)}$	0.051	0.068	0.254	0.076	0.110	0.195	0.085	0.161
$g_{i,t}^{(10)}$	0.073	0.107	0.226	0.061	0.223	0.204	0.098	0.009
$g_{i,t}^{(25)}$	0.022	0.057	0.315	0.096	0.275	0.184	0.046	0.005
$g_{i,t}^{(49)^a}$	0.025	0.037	0.28	0.113	0.351	0.173	0.018	0.003
$g_{i,t}^{(74)^a}$	0.020	0.033	0.264	0.118	0.350	0.188	0.023	0.002
$g_{i,t}^{(89)}$	0.021	0.052	0.276	0.079	0.263	0.264	0.041	0.003
$g_{i,t}^{(99)}$	0.032	0.104	0.261	0.064	0.237	0.229	0.068	0.004
$g_{i,t}^{(100)}$	0.067	0.139	0.234	0.045	0.200	0.222	0.089	0.006

^aThese growth categories are used as base case in the regression analysis

Table 6 Transition probabilities for growth by percentile during 1999-2002, 2002-2005, and 2005-2008, micro firms

	$g_{i,t+3}^{(1)}$	$g_{i,t+3}^{(10)}$	$g_{i,t+3}^{(25)}$	$g_{i,t+3}^{(49)^a}$	$g_{i,t+3}^{(74)^a}$	$g_{i,t+3}^{(89)}$	$g_{i,t+3}^{(99)}$	$g_{i,t+3}^{(100)}$
$g_{i,t}^{(1)}$	0.001	0.042	0.051	0.227	0.248	0.084	0.250	0.097
$g_{i,t}^{(10)}$	0.002	0.049	0.057	0.318	0.261	0.088	0.211	0.014
$g_{i,t}^{(25)}$	0.007	0.094	0.173	0.204	0.270	0.184	0.063	0.004
$g_{i,t}^{(49)^a}$	0.003	0.073	0.092	0.450	0.186	0.112	0.081	0.003
$g_{i,t}^{(74)^a}$	0.004	0.072	0.111	0.264	0.370	0.102	0.073	0.003
$g_{i,t}^{(89)}$	0.010	0.085	0.233	0.187	0.214	0.220	0.048	0.003
$g_{i,t}^{(99)}$	0.012	0.199	0.141	0.177	0.197	0.195	0.075	0.004
$g_{i,t}^{(100)}$	0.056	0.108	0.231	0.055	0.196	0.253	0.091	0.011

^aThese growth categories are used as base case in the regression analysis

Table 7 Transition probabilities for growth by percentile during 1999-2002, 2002-2005, and 2005-2008, small firms

	$g_{i,t+3}^{(1)}$	$g_{i,t+3}^{(10)}$	$g_{i,t+3}^{(25)}$	$g_{i,t+3}^{(49)^a}$	$g_{i,t+3}^{(74)^a}$	$g_{i,t+3}^{(89)}$	$g_{i,t+3}^{(99)}$	$g_{i,t+3}^{(100)}$
$g_{i,t}^{(1)}$	0.014	0.117	0.136	0.150	0.162	0.144	0.150	0.128
$g_{i,t}^{(10)}$	0.046	0.103	0.246	0.083	0.194	0.202	0.112	0.014
$g_{i,t}^{(25)}$	0.025	0.061	0.306	0.106	0.267	0.201	0.032	0.002
$g_{i,t}^{(49)^a}$	0.020	0.036	0.306	0.137	0.310	0.169	0.021	0.002
$g_{i,t}^{(74)^a}$	0.017	0.041	0.272	0.112	0.336	0.195	0.024	0.002
$g_{i,t}^{(89)}$	0.019	0.051	0.265	0.086	0.278	0.255	0.044	0.002
$g_{i,t}^{(99)}$	0.034	0.089	0.272	0.060	0.203	0.257	0.079	0.006
$g_{i,t}^{(100)}$	0.076	0.102	0.237	0.041	0.215	0.235	0.086	0.008

^aThese growth categories are used as base case in the regression analysis

Table 9 Results from the *first difference least squares* (FDLS) estimator, all firms, alternate periods

	1999-2008 (3 year)		1998-2007 (3 year)		1997-2006 (3 year)		1997-2008 (Annual)	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)
	$\widehat{\beta + \Gamma_{q_j}}$	$\gamma_{q_j}^a$						
$\Delta g_{i,t-3}$	1.023*** (0.001)	0.012*** (0.000)	1.014*** (0.001)	0.007*** (0.000)	1.019*** (0.001)	0.009*** (0.003)	1.000*** (0.000)	-0.000 (0.000)
$D_{q_1} \Delta g_{i,t-3}$	0.823*** (0.046)	-0.088*** (0.023)	0.866*** (0.050)	-0.067*** (0.025)	0.845*** (0.052)	-0.078*** (0.026)	0.969*** (0.018)	-0.016* (0.010)
$D_{q_{2-10}} \Delta g_{i,t-3}$	0.948*** (0.003)	-0.026*** (0.003)	0.952*** (0.007)	-0.024*** (0.003)	0.938*** (0.006)	-0.031*** (0.003)	0.950*** (0.003)	-0.025*** (0.001)
$D_{q_{11-25}} \Delta g_{i,t-3}$	0.970*** (0.003)	-0.015*** (0.001)	0.975*** (0.003)	-0.012*** (0.002)	0.976*** (0.003)	-0.012*** (0.002)	0.956*** (0.001)	-0.022*** (0.001)
$D_{q_{75-89}} \Delta g_{i,t-3}$	0.989*** (0.002)	-0.005*** (0.001)	0.985*** (0.003)	-0.008*** (0.001)	0.988*** (0.002)	-0.006*** (0.001)	1.045*** (0.001)	0.023*** (0.001)
$D_{q_{90-99}} \Delta g_{i,t-3}$	0.985*** (0.006)	-0.007** (0.003)	0.988*** (0.006)	-0.006*** (0.003)	1.000*** (0.006)	-0.000 (0.003)	0.863*** (0.002)	-0.069*** (0.001)
$D_{q_{100}} \Delta g_{i,t-3}$	0.724*** (0.040)	-0.138*** (0.020)	0.789*** (0.050)	-0.126*** (0.025)	0.709*** (0.062)	-0.146*** (0.031)	0.702*** (0.020)	-0.149*** (0.010)
Constant	0.037*** (0.001)		0.0389*** (0.001)		0.044*** (0.001)		0.008*** (0.001)	
Interc. dummy	yes		yes		yes		yes	
Fixed effects	yes		yes		yes		yes	
Year dummy	yes		yes		yes		yes	
Obs	244,367		232,501		227,162		1,623,983	
R ²	0.921		0.920		0.921		0.901	

^aThe autocorrelation function is computed from $\gamma_{q_j} = 0.5(1 - \beta - \Gamma_{q_j})$

* Statistical significant at the 10%-level; ** Statistical significant at the 5%-level; *** Statistical significant at the 1%-level

Table 10 Results from the *first difference least squares* (FDLS), firms divided by size and business-group membership, 1999-2008 (3 year).

	Micro firms		Small firms		Median/Large firms		Non-business group	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	(4a)	(4b)
	$\widehat{\beta} + \widehat{\Gamma}_{q_j}$	$\gamma_{q_j}^a$						
$\Delta g_{i,t-3}$	1.013*** (0.001)	0.006*** (0.000)	1.017*** (0.003)	0.008*** (0.001)	1.009*** (0.004)	0.005** (0.002)	1.019*** (0.001)	0.009*** (0.000)
$D_{q_1} \Delta g_{i,t-3}$	0.962*** (0.036)	-0.019 (0.018)	0.897*** (0.076)	-0.052 (0.038)	0.809*** (0.232)	-0.096 (0.116)	0.858*** (0.065)	-0.071** (0.032)
$D_{q_{2-10}} \Delta g_{i,t-3}$	0.957*** (0.007)	-0.022*** (0.003)	0.966*** (0.020)	-0.017* (0.010)	0.914*** (0.037)	-0.043** (0.018)	0.945*** (0.007)	-0.028*** (0.004)
$D_{q_{11-25}} \Delta g_{i,t-3}$	0.964*** (0.004)	-0.018*** (0.002)	0.953*** (0.006)	-0.024*** (0.003)	0.971*** (0.010)	-0.015*** (0.005)	0.965*** (0.004)	-0.017*** (0.002)
$D_{q_{75-89}} \Delta g_{i,t-3}$	0.972 (0.003)	-0.014*** (0.002)	1.029*** (0.005)	0.015*** (0.003)	1.025*** (0.008)	0.013*** (0.00)	0.977*** (0.003)	-0.011*** (0.002)
$D_{q_{90-99}} \Delta g_{i,t-3}$	0.941*** (0.007)	-0.029*** (0.004)	0.969*** (0.015)	-0.015** (0.007)	0.996*** (0.026)	-0.002 (0.013)	0.974*** (0.008)	-0.013*** (0.004)
$D_{q_{100}} \Delta g_{i,t-3}$	0.845*** (0.036)	-0.077*** (0.018)	0.597*** (0.048)	-0.201*** (0.024)	0.548*** (0.108)	-0.226*** (0.054)	0.872*** (0.070)	-0.064*** (0.035)
Constant	0.021*** (0.001)		0.127*** (0.002)		0.121*** (0.005)		0.024*** (0.001)	
Interc. dummy	yes		yes		yes		yes	
Fixed effects	yes		yes		yes		yes	
Year dummy	yes		yes		yes		yes	
Obs	192,888		35,785		8,074		171,668	
R ²	0.931		0.926		0.897		0.926	

^aThe autocorrelation function is computed from $\gamma_{q_j} = 0.5(1 - \beta - \Gamma_{q_j})$

* Statistical significant at the 10%-level. ** Statistical significant at the 5%-level. *** Statistical significant at the 1%-level.

Fig. 1 Growth rate distribution of all firms 1999-2002, 2002-2005 and 2005-2008

