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Bursting into life: firm growth and growth persistence by age

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Abstract Is firm growth more persistent for young or
old firms? Theory gives us no clear guidance, and
previous empirical investigations have been hampered
by a lack of detailed data on firm age, as well as a non-
representative coverage of young firms. We overcome
these shortcomings using a rich dataset on all limited
liability firms in Sweden during 1998–2008, covering
firms of all ages and information on registered start year.
Sales growth for new ventures is characterized by pos-
itive persistence, which quickly turns negative as firms
get older. Young firms are more likely to have two
consecutive periods of positive growth. While new
firms experience an early burst of sustained growth,
older firms have more erratic growth paths.

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1 Introduction

A key indicator of the performance of new ventures is
their post-entry growth (Audretsch 1995; Parker 2004).
The aim of this paper is to contribute to our knowledge of
how growth patterns vary with age. Building on previous
research into the growth paths of new ventures (Delmar
et al. 2003; Coad et al. 2013a), we provide new evidence
on how growth persistence is moderated by firm age.

This paper addresses recent concerns that the charac-
teristics of new firm growth remain poorly understood
(McKelvie and Wiklund 2010), which is partly due to a
lack of high quality data on young firms. The paucity of
research into how firm growth varies with age can be
explained by two data-related issues. First, there is lim-
ited availability of data on firm age: Headd and
Kirchhoff (2009, p548) recently commented on "the
dearth of information by business age" and explained
that "[s]imply stated, industrial organization and small
business researchers are deprived of firm-age data."
Relatedly, Decker et al. (2014, p3) observe that infor-
mation on firm age has only recently been added to
administrative databases. Second, it is very difficult to
obtain representative data on very young firms, since
they are often only included in the dataset when they
exceed a certain threshold size (Coad et al. 2013b). We
maintain that our exploratory search for empirical regu-
larities requires analysis of large-sample data (cf Helfat
2007, p189).

We overcome previous data limitations by using a
unique and rich dataset compiled from the Swedish
Patent and Registration Office (PRV) on all limited

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liability firms during 1998–2008. The data cover all young firms and also include information on the registered start year. While previous research has had difficulties in obtaining data on the early years of new ventures (for a survey, see Bamford et al. 2004, their Table 1), we are thus in a unique position to look at growth paths of firms of all ages.

Previous research linking firm age to firm growth generally took the form of adding firm age as an explanatory variable in a firm growth regression model, usually finding that younger firms have faster expected growth rates (e.g., Fizaine 1968; Evans 1987; Dunne et al. 1989; Robson and Bennett 2000; Yasuda 2005). Recent work has even suggested that, controlling for age, firm size no longer has any systematic relationship with firm growth, such that it is age, rather than size, that best explains a firm's growth rate (Haltiwanger et al. 2013; Lawless 2014).[1] Dunne et al. (1989) also observed that a firm's growth rate variance decreases with age. A few studies have investigated the effect of age on growth across the growth rate distribution, finding that young firms are equally likely to experience decline as old firms, but that young firms are more likely to experience fast growth than old firms (Reichstein et al. 2010; Coad et al. 2013b; Barba Navaretti et al. 2014). Daunfeldt et al. (2014) also observed that high-growth firms in general were younger than other firms, irrespective of whether employment, sales, labor productivity, or value added was used as growth indicator.

Another strand of literature has focused on growth rate autocorrelation. The possible existence of growth-rate autocorrelation has prompted a large number of empirical investigations (e.g., Ijiri and Simon 1967; Singh and Whittington 1975; Dunne and Hughes 1994; Goddard et al. 2002; Coad 2007; Coad and Hölzl 2009; Capasso et al. 2014; Bianchini et al. 2016), because of interest in understanding firms longer-term growth trajectories, as well as concerns about industrial concentration. Indeed, "serial correlation in firm growth rates ... is of considerable economic interest and deserves to be examined in its own right." (Singh and Whittington 1975, p17). Early studies (Ijiri and Simon 1967; Singh and Whittington 1975), using

mostly data on large manufacturing firms, indicated that the process of firm growth was characterized by positive autocorrelation. Results from recent studies are more ambiguous, with some finding that firm growth is characterized by positive autocorrelation rates (Dunne and Hughes 1994) and others negative autocorrelation (Goddard et al. 2002; Bottazzi et al. 2011), while still others conclude that there is no growth persistence (Almus and Nerlinger 2000; Lotti et al. 2003). Coad (2007), Coad and Hölzl (2009) and Capasso et al. (2014) investigate the role played by firm size using quantile regression techniques. The results from these studies indicate that autocorrelation in general is negative for small firms, whereas large firms show positive or no persistence in growth rates. The highest negative autocorrelation was found among the 10% fastest growing firms, making sustained high growth rates a very unlikely growth process. This result is also supported by Parker et al. (2010), Hölzl (2014) and Daunfeldt and Halvarsson (2015), who have found that high-growth firms are essentially "one-hit wonders."

The most closely related paper to our own is probably Coad et al. (2013b) who present some preliminary results on how growth rate persistence changes with firm age, reporting that sales-growth autocorrelation was positive for firms that were less than 5 years old, but soon turned negative, and remained negative, for older firms. However, these authors cautioned that survivor bias and selection bias could be driving these results, such that young firms with relatively high growth rates were over-represented in their data.

We contribute to the literature by providing new evidence on how the growth-rate distribution changes with firm age, including how the first four moments change with age, and providing findings on how growth rate autocorrelation varies with age. We present robust evidence that young firms experience a sudden burst of growth shortly after entry, and that soon afterwards their growth rates slow down and become more erratic (in the sense of experiencing negative autocorrelation).

Our results thus indicate that young firms are characterized by positive growth autocorrelation in the years immediately after entry, but that the autocorrelation coefficient quickly turns negative and remains negative as firms get older. Nascent ventures, therefore, enjoy a brief spell of positive growth persistence—a sort of "success-breeds-success" dynamic—which lasts for about 5 years, until persistence becomes negative. This

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[1] In fact, this was already emphasized by Fizaine (1968) when investigating the growth of establishments in the French region of Bouches-du-Rhône.

finding can be tentatively linked to the struggle for new ventures to grow and overcome the vulnerabilities related to their initial small scale (Stinchcombe 1965). We can thus reject the hypothesis that older firms should have a higher degree of growth persistence due to learning effects, better foresight, or longer-range planning horizons. Instead our results support theories arguing that older firms might have difficulties in adapting their strategies to changing market conditions, whereas new firms need to grow in order to achieve a minimum efficient scale.

The paper is organized as follows. Section 2 contains our theoretical background. Section 3 describes our data, and Section 4 presents our methodology. Our results and robustness analyses are in Section 5, and Section 6 concludes.

2 Background

Autocorrelation in growth rates is an important feature of firm growth. Theoretical models of firm growth, such as Gibrat's "Law of Proportionate Effect" (Gibrat 1931) or variations on this model (e.g., Levinthal 1991), first suggested that there is no autocorrelation in growth rates, such that growth in one period is independent of growth in the following period. The intuition behind this assumption of no autocorrelation could be explained as follows. Young firms are exposed to business challenges for which they may be initially unprepared; they are vulnerable to unexpected shocks on all sides, which may result in an erratic growth performance that is characterized by the "prevalence of interruptions to growth" (Garnsey and Heffernan 2005, p675). "New firms are hampered by their need to make search processes a prelude to every new problem they encounter" (Garnsey 1998, p541)—which suggests that new firm growth lacks continuity and suggests that superior growth performance in 1 year need not imply superior growth performance in the following year. Young firms with under-developed routines and capabilities may therefore be expected to grow in unpredictable and erratic ways—i.e., the lack of persistence in new venture growth would correspond to a lack of autocorrelation in growth rates for young firms.

Hypothesis 1a: There is no autocorrelation in the growth rates of young firms.

In essence, positive growth rate autocorrelation (i.e., when growth over the period *t-2:t-1* is positively correlated with growth over the period *t-1:t*) corresponds to a case of increasing returns to growth, or a "virtuous cycle" of success-breeds-success (or, alternatively, failure-breeds-failure), where any growth (or decline) that a firm achieved in 1 year will enhance the expected growth (or decline) in the following year. Positive growth autocorrelation corresponds to sustained smooth growth profiles, whereas negative growth autocorrelation corresponds to erratic growth paths (where positive growth in 1 year decreases the expected growth rate in the following year).

Young firms have traditionally been associated with a "liability of newness" (Stinchcombe 1965) as they struggle to develop routines, learn new roles, forge new relationships with customers, and—more generally—establish themselves in their new environment. Part of the liability of newness comes from their liability of smallness, whereby new firms are often relatively small, strive to grow in order to quickly reach a larger, more efficient scale of operation (close to, or above, the "Minimum Efficient Scale"). Indeed, empirical work has consistently found that young firms have higher average growth rates than older firms (Fizaine 1968; Haltiwanger et al. 2013; Lawless 2014). Hence, young firms could be expected to have a sustained period of relatively high growth rates in the years after entry:

Hypothesis 1b: young firms display positive growth rate autocorrelation.

Older firms, in contrast, are prone to suffer from a "liability of obsolescence" and also a "liability of senescence" (Barron et al. 1994). This implies lower growth persistence for old firms, since they may have problems adapting their strategies to changing business conditions as well as increasing inertia and organizational rigidities. Older firms may therefore be buffeted around by business phenomena beyond their control, which thwart the continuity of any longer-term business plans they may have. In the years after entry, young firms might struggle to reach a "minimum efficient scale" (MES) and achieve economies of scale (Lotti et al. 2009). As time goes by, however, their initial burst of energy may fade, and once they have survived the first few years and have settled into their new organizational routines, their growth will lose its momentum. Previous evidence has shown that the growth of older firms is more random and harder to predict (Coad et al. 2016). While younger firms might display positive autocorrelation in their early years, older firms that

have become well-established in their niches may stabilize at a certain size, and any growth that occurs later lacks persistence and may correspond to mere fluctuations around a steady-state size (where growth in 1 year would be unrelated to growth in the next year). Hence:

Hypothesis 2a: there is no autocorrelation in the growth rates of old firms.

An alternative view, however, would be that older firms have more experience and foresight when it comes to their business environment, which leads to longer planning horizons, and have built up routines and capabilities that may lead to sustained superior performance, and can therefore be expected to have smoother growth paths with fewer bumps and surprises (that is—more positive autocorrelation in their growth rates). Older firms are also more likely to purchase insurance to protect themselves from unexpected shocks (such as hurricane Sandy: see Collier et al. 2016). Learning-by-doing models (Arrow 1962; Sorensen and Stuart 2000; Chang et al. 2002) furthermore suggest that older firms may benefit from their greater business experience and therefore can be expected to have a higher degree of growth persistence than their younger counterparts. Although the relationship between growth persistence and age has so far escaped attention, nevertheless the evidence on how growth persistence varies with size suggests that larger firms have smoother growth profiles than smaller firms (Coad 2007; Coad and Hölzl 2009). To the extent that age and size are closely related (e.g., Greiner 1998), we might also expect that older firms will have positive growth-rate autocorrelation.

Hypothesis 2b: old firms display positive growth rate autocorrelation.

3 Data

3.1 Data description

The main challenges when investigating the effects of firm age are data availability and the necessity of a comprehensive representation of young firms (Headd and Kirchhoff 2009; Decker et al. 2014). In order to overcome these challenges, we chose to use the PAR-dataset, which comprises all Swedish limited liability firms during 1997–2010. Swedish administrative datasets have previously been shown to be an unusually rich information source for entrepreneurship research (e.g., Davidsson et al. 2009; Folta et al. 2010).

In Sweden, all limited liability firms are required by law to submit an annual report to the Swedish patent and registration office (PRV), and PAR, a Swedish consulting firm, gathered this information from PRV. The dataset thus covers all limited liability firms, which means that young firms are not under-represented as in many other studies (e.g., Huergo and Jaumandreu 2004; Coad et al. 2013b). The data include all variables that can be found in the annual reports (e.g., number of employees, sales, financial ratios), industry classification codes, M&A activity, and whether the firm is part of a business group.

Another attractive feature of the dataset is that it includes information on the registered start year, with the oldest firm being registered already in 1877. For firms that are registered during the study period 1998 to 2008, we even have information on the month of the first accounting year. This means that we can identify firms during their first year of business and determine firm age exactly for companies that started during 1998–2008. This level of detail allows us to observe firms within their first year as a startup. For firms that registered prior to 1998, we cannot identify the correct age down to a single month and therefore rely on the registered start year to determine a firm's age.[2] We restrict our analysis to active firms ($i = 1, \ldots, n$), which we define as firms that have at least one employee and positive sales. We focus on sales growth rather than employment growth, because the employment growth of micro firms is heavily affected by "lumpiness" in growth due to the integer constraints that arise from data on employee headcounts (Coad et al. 2013a).[3] More specifically, we measure firm growth by taking the log-difference of firm size, which is the usual way of calculating growth rates (Tornqvist et al. 1985; Coad 2009), i.e.,

$$\text{growth}_{i,t} = log\left(size_{i,t}\right) - log\left(size_{i,t-1}\right) \qquad (1)$$

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[2] This latter approach to determine a firm's age is still highly accurate, but it means that for older firms our age variable cannot account for the possibility that a firm has changed the periodicity of their split financial year and consequentially measure age with a possible error of at most ±1 year.
[3] These integer restrictions affecting employment growth data are particularly problematic for the computation of quantile regressions. In a further robustness analysis, however, we apply OLS regressions to employment growth data, and the results obtained were similar in that the autocorrelation coefficient is highest in the early years and quickly decreases (although for most ages, the autocorrelation coefficient was not clearly negative but close to zero).

where $size_{i,t}$ is inflation adjusted $sales_{i,t}$. Employment and sales are the two growth indicators that are most commonly used within the firm growth literature (Delmar 1997). Although sales and employment can be thought of as output and input variables in the production function, they are still modestly correlated (Shepherd and Wiklund 2009). The correlation for all years between sales growth and employment growth in our data is 0.35.

With few exceptions, most firm growth studies rely on measures of total growth (i.e., the sum of organic and acquired growth) since they do not have access to any data on mergers and acquisitions (Coad et al. 2014). However, mergers and acquisitions (M&As) are likely to be related to the age of the firm and can thus influence the relationship between firm age and growth persistence. Fortunately, the database includes information on M&As and we therefore choose to exclude all firms from that registered any such activity during the study period. This ensures us that we capture how firm age is related to organic growth autocorrelation and not to growth episodes that occur through external growth via M&As. We also include a dummy variable to capture differences between firms that operated in a business group in the beginning of the study period and those that did not. In contrast to most previous studies, we can thus focus on organic growth and also control whether the firm was part of a business group at the beginning of the growth period studied.

Our main variable of interest is firm age, which is defined as the observation year minus the registered start year. Compared to other studies on firm age, we do not need to work with left-censored age distributions due to our complete coverage. The extensive information of firm age is unique and should enable us to accurately assess the age effect on growth persistence.

3.2 Non-parametric plots

The age distribution for the population of firms in 2008 is presented in Fig. 1, showing that most firms are young. This is to be expected, since we know that young firms have high exit rates (Lotti et al. 2003), with about 50% of firms exiting in the first 3 years (Anyadike-Danes and Hart 2014; Coad 2017). Except for the humps around ages 20 and 40, the distribution appears to show roughly exponential decay.[4] The humps can be

explained by legal changes in Sweden that increased the minimum amount of capital required to start an incorporation.[5]

Turning to our sample, the mean age in 2008 is 14.4 (median = 14 years) and the corresponding mean in 2000 is 14.4 (median = 11 years), which partly reflects the shifts of the hump around 1995.[6] With a standard deviation of age equal to 13.2 (in 2008), we find that the mean and standard deviation of age are fairly close in magnitude, but not equal as would be the case for strictly exponentially distributed variables. The oldest firms in the sample are 111 years old, and there are 30 such firms, which means that we can completely rule out right-censoring, especially since our primary focus is on firms with ages of up to 40 years.

Figure 2 shows the kernel density plots for annual sales growth rates for different age groups during 2008. Plotted on semi-log axes, the growth-rate distribution exhibits the familiar "tent-shape" (Stanley et al. 1996; Bottazzi and Secchi 2006) which indicates that the growth rate distribution is far from the Gaussian case and instead is Laplace-distributed. Moreover, the distribution of the youngest firms (age <5 years) is different from that of older firms, because it has more probability mass with positive growth rates. This indicates that younger firms are more likely than older firms to experience fast sales growth rates, confirming earlier results (Coad et al. 2013b; Barba Navaretti et al. 2014). An interesting observation is that the numbers of young firms in the middle of the growth rate distribution (i.e., with growth rates close to zero) are also far fewer than what can be found in the distributions of older firms. This implies that younger firms also are less likely to experience marginal growth rates compared to older firms. Finally, the left tail of the growth rate distribution seems roughly invariant to firm age, suggesting that younger firms have almost the same likelihood of facing fast rates of decline as older firms.

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[4] For simplicity, we overlook the fact that the exponential is a continuous distribution whereas our age data is discrete.

[5] In 1975, Sweden increase the minimum amount of capital required to start an incorporation from 5000 SEK to 50,000 SEK. This amount was increased once more in 1995 from 50,000 SEK to 100,000 SEK. Firms that registered prior to January 1 in 1995 were exempt from increasing the equity to 100,000 SEK until 1998. The reason we still see an increase in 1995 (until the last of July) is because a newly registered company had a 6-month period to have a first statutory meeting of the board. This means that a firm could have a registration date in June of 1995, but still qualify for 50,000 SEK in equity. As for the increase observed in the month of July, it is due to the registration of a large number of so-called shelf-companies.

[6] The mode is not reported here, because the distribution is multimodal.

Fig. 1 Frequency plot over firm age for the whole population in 2008. Note: A discrete frequency plot over firm age (one bar for each age) for the population of 316,298 incorporated firms registered in 2008
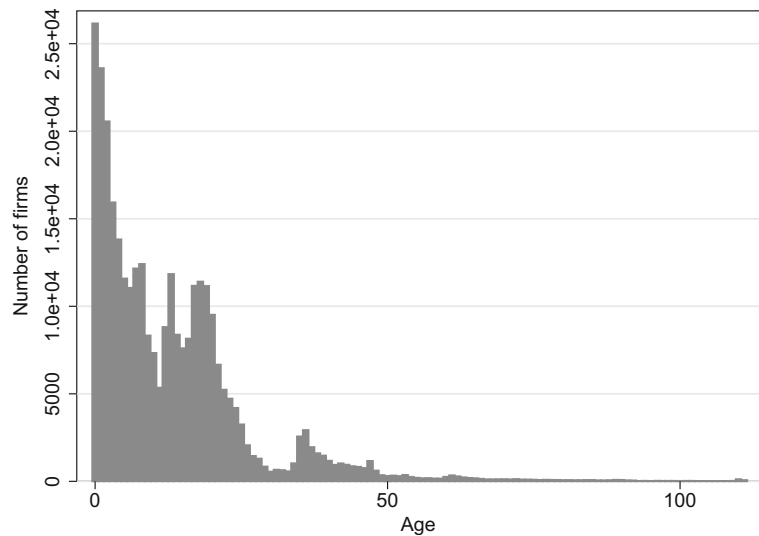

Figure 3 contains further analysis of how the first four moments of the growth rate distribution (i.e., the average, standard deviation, skewness, and kurtosis) vary with age. The top-left panel shows that the average growth rate is the highest in the first observed period (i.e., year 2),[7] after which it quickly stabilizes at a level which is slightly negative. The beneficial effects of youth on growth rate therefore appear to be short-lived (see also Haltiwanger et al. 2013 and Lawless 2014). The top-right plot of Fig. 3 shows how the standard deviation of firm growth decreases comparatively steadily over the first 40 years. The skewness of growth rates starts at values of close to zero in year 2 and appears to generally become more negative in the years until year 40. In other words, the growth rate distribution may be relatively symmetric to start with, but as firms age, it becomes more negatively skewed, with firm decline overshadowing firm growth. Finally, the fourth moment of the growth rate distribution (i.e., the kurtosis, shown in the bottom right plot of Fig. 3) shows that the kurtosis generally increases in the years after entry. This complements the earlier finding that the standard deviation decreases—hinting that the growth rate distribution becomes slightly more heavy-tailed (but with lower variance) and further from the Gaussian case as firms age.

The higher dispersion in growth rates among the very youngest firms can also be seen in Table 1 that shows some descriptive statistics for the sales-growth variable.

Firms less than 10 years old show positive average growth rates and higher standard deviation than older age categories (which have negative average growth rates).

One of the most important dimensions for distinguishing between heterogeneous firms (and also the growth performance of these firms) is firm size. Small firms have been repeatedly observed to grow faster than large firms (Sutton 1997), and growth rate autocorrelation has also been shown to depend on firm size (Coad 2007). We therefore split our sample into firms with, on average, up to 4 employees, 5–9 employees, and 10 employees or more, over the periods $t-1$ and $t-2$. Descriptive statistics of growth rates for each size class are presented in Table 5 in the "Appendix" section. The positive average growth rates observed for firms with age less than 10 in Table 1 remain for each size class, whereas the negative average growth rates in Table 1 for firms aged 10+ seem to be driven by firms with fewer than five employees.

In order to identify the effect of firm age on growth persistence, we also control for industry variation (at the 2-digit NACE industry level) in average industry growth rate, market concentration (measured using a Herfindahl concentration index), entry rate and exit rate. We also control for the effect on firm growth persistence of being part of a larger business group. Descriptive statistics of all control variables are presented in Table 2.

To get a first impression of the relationship between intertemporal growth rates, we look at the bivariate density of sales growth of consecutive

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[7] Growth is calculated as a function of both size at time t, and size at time t-1; hence, the first observation for growth is in year 2.

Fig. 2 Density plot of sales growth for firms of different age groups in 2008. Note: Density plot with an epanechnikov kernel function at 50 points, delimited at ±2
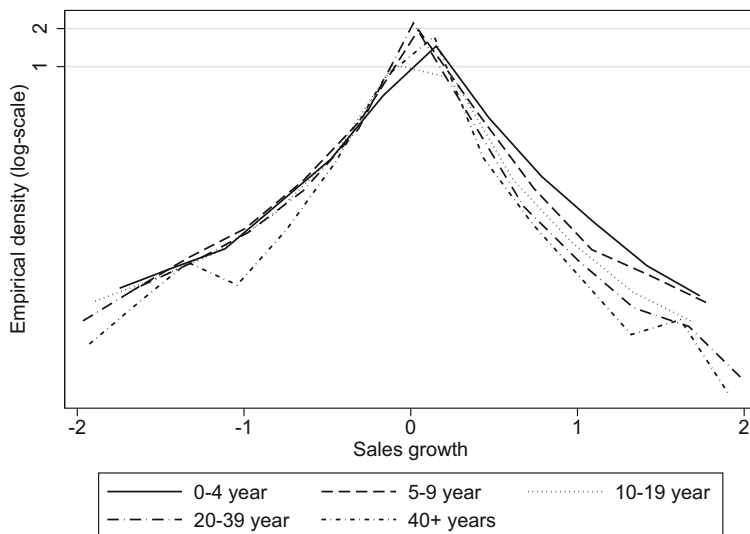
annual growth rates. Figure 4 is a representation of the bivariate density of sales growth in periods t and $t-1$ and is in itself an important contribution to empirical work on growth autocorrelation, because it provides a "big picture" summary representation of

the frequencies of growth paths across two periods. The frequency is projected into the plane on a 0.1×0.1 grid by the aid of a contour plot, illustrated through eight shades of gray into equidistant logarithmic categories, starting from 1 firm. Growth in
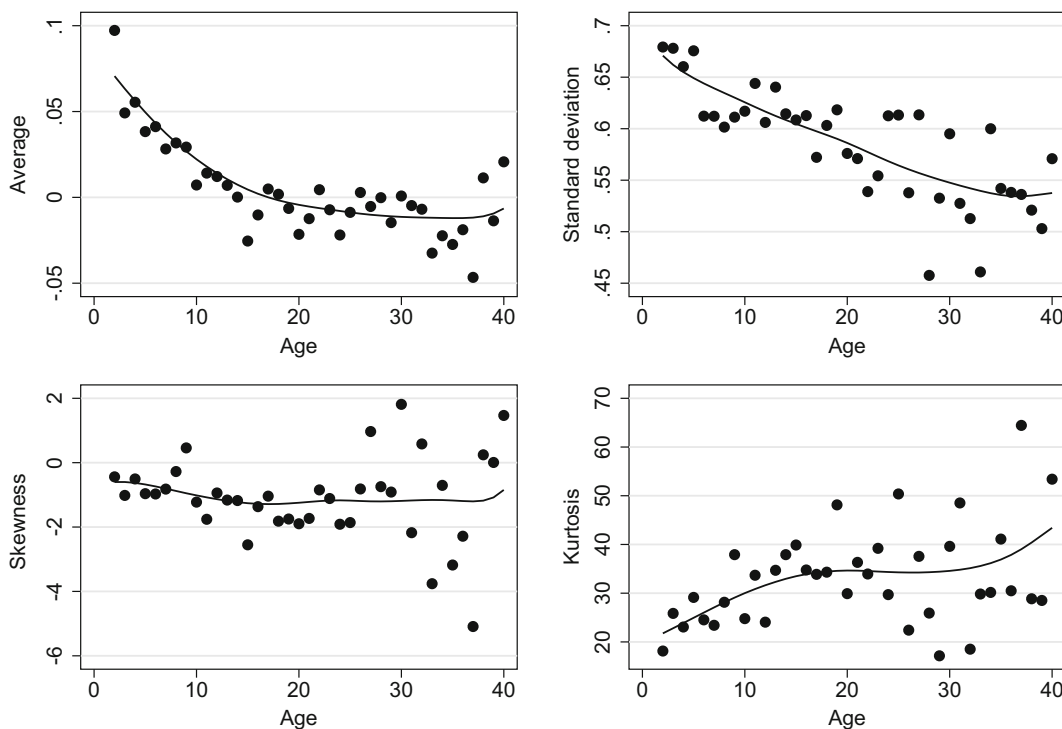

Fig. 3 Mean, standard deviation, skewness, and kurtosis of growth rates as a function of age 2008–2007. Note: The plots correspond to the first four moments for firms of ages 2 to 40. Each plot is fitted with a nonlinear trend based on locally weighted regressions (lowess in Stata)

Table 1 Description of sales growth by age categories (2008)

All firms	Obs	Mean	SD	Min	Q25	Median	Q75	Max
0–4 year	22,324	0.068	0.673	−8.674	−0.094	0.086	0.276	6.764
5–9 year	33,250	0.034	0.624	−8.249	−0.107	0.063	0.218	8.688
10–19 years	57,765	0.000	0.612	−9.755	−0.111	0.048	0.181	7.762
20–39 year	34,710	−0.013	0.561	−8.552	−0.108	0.037	0.153	7.594
40+ years	9390	−0.017	0.517	−7.224	−0.083	0.038	0.130	7.209
All firms	157,439	0.013	0.608	−9.755	−0.106	0.052	0.190	8.688

either period is restricted to the range from −2 to 2, and every non-white shade indicates that some firms are present. The darker the color, the higher the frequency of firms with the observed intertemporal pair of sales growth rates.

The bivariate distribution is unimodal with a dark center, indicating that many firms have growth rates close to zero in both periods. Almost all areas of the grid are covered, which means that most configurations of consecutive growth rates are represented. In each corner, however, we see that the shading becomes lighter in color, which suggests that only a few firms experience extreme growth rates in consecutive periods (whether it be extreme positive or extreme negative growth).

Figure 4 shows the probability of growth in two consecutive periods, but it does not include information about firm age. Since we are interested in understanding the relationship between growth-rate autocorrelation and firm age, we change the shading parameter that determines the contour lines. Instead of using frequency of firms, Fig. 5 lets the shading parameter represent changes in median age.[8] The plot can be split into four quadrants. For example, firms in the top-right (TR) quadrant (with growth in the range [0,2] in both periods) experienced positive growth rates in both 2007 and 2008. If for example hypothesis 1b holds, which states that young firms experience positive autocorrelation, then we would observe lighter colored areas in the top-right (TR) and/or bottom-left (BL) quadrants in Fig. 5. On the other hand, should hypothesis 2b hold, we would instead observe darker shading in the diagonal quadrants: top-right (TR) and/or bottom-left (BL). Looking

at the figure, we can discern at least one clear tendency. In the TR quadrant, there is a noticeable amount of lighter shaded areas, suggesting that young firms are more likely to experience positive growth rates in both periods $t-1$ and t.

It is worthwhile to test for statistically significant differences in the densities of average age for each of the four quadrants. If indeed young firms are over-represented in the TR quadrant, we would see the weighted density corresponding to TR to be left-leaning, which is clearly the case if we look at Fig. 6.[9] From the same figure, we see a second tendency, although much subtler, with older firms (that are represented by dark shading in Fig. 5) being over-represented in the BL quadrant, meaning that they are more likely to experience negative growth rates in the periods $t-1$ and t. Both of these findings offer early support for hypotheses 1b and 2b, but for different reasons: while Fig. 6 suggests that both young and old firms experience positive autocorrelation, positive growth rates in consecutive years are more likely for younger firms, whereas negative growth rates in consecutive years are more likely for older firms. Differences between the distributions in Fig. 6 can be formally tested with pairwise two-sided Kolmogorov-Smirnov tests accompanied with standard t tests. Except for the TL and BR distributions, all pairwise combinations are significantly different (results not shown here). Thus, the contour plots offer some early support for hypothesis 1b (and weaker support for hypothesis 2b). While graphical models are well-

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[8] Since the distribution of age is skewed, using the mean instead of the median could be problematic if there are firms with high age in a grid-box that otherwise contains mostly young firms.

[9] Since median age is computed with different numbers of observations over the grid, the densities in Figure 6 are therefore weighted giving more weights to cells in the grid that contains more observations. The weights are constructed by counting the number of observations in each grid-box over which the median age is computed. The resulting counts are then entered as analytical weights [aweights] in the contour plot.

Table 2 Description of industry variables defined at the 2-digit NACE level (2008) and sales

Variables	Obs	Mean	SD	Min	Q25	Median	Q75	Max
Industry growth	157,439	0.004	0.049	−0.291	−0.027	0.006	0.027	1.112
Herfindahl	157,439	0.026	0.054	0.002	0.005	0.014	0.028	0.959
Entry rate	157,439	0.025	0.016	0.000	0.016	0.019	0.030	0.244
Exit rate	157,439	0.069	0.018	0.000	0.052	0.074	0.082	0.154
Business grp [a]	157,439	0.254	0.435	0.000	0.000	0.000	1.000	1.000
ln(sales)	157,439	12.924	1.768	4.758	11.827	12.840	13.971	22.998

[a] Business Grp is defined at the firm level

suited for exploratory empirical research (Bettis et al. 2014), the next section tests our hypotheses in more detail using multivariate regressions that include control variables. By combining visual analysis and rigorous statistical/econometric analysis, we seek to provide richer insights into the robustness and the economic and statistical significance of the hypotheses.

4 Regression methodology

This paper follows in the tradition of modeling firm growth as a stochastic process (Gibrat 1931; Levinthal 1991; Geroski 2000; Coad et al. 2013a; Denrell et al. 2015). At any point in time, even if there is a multitude of different factors (internal
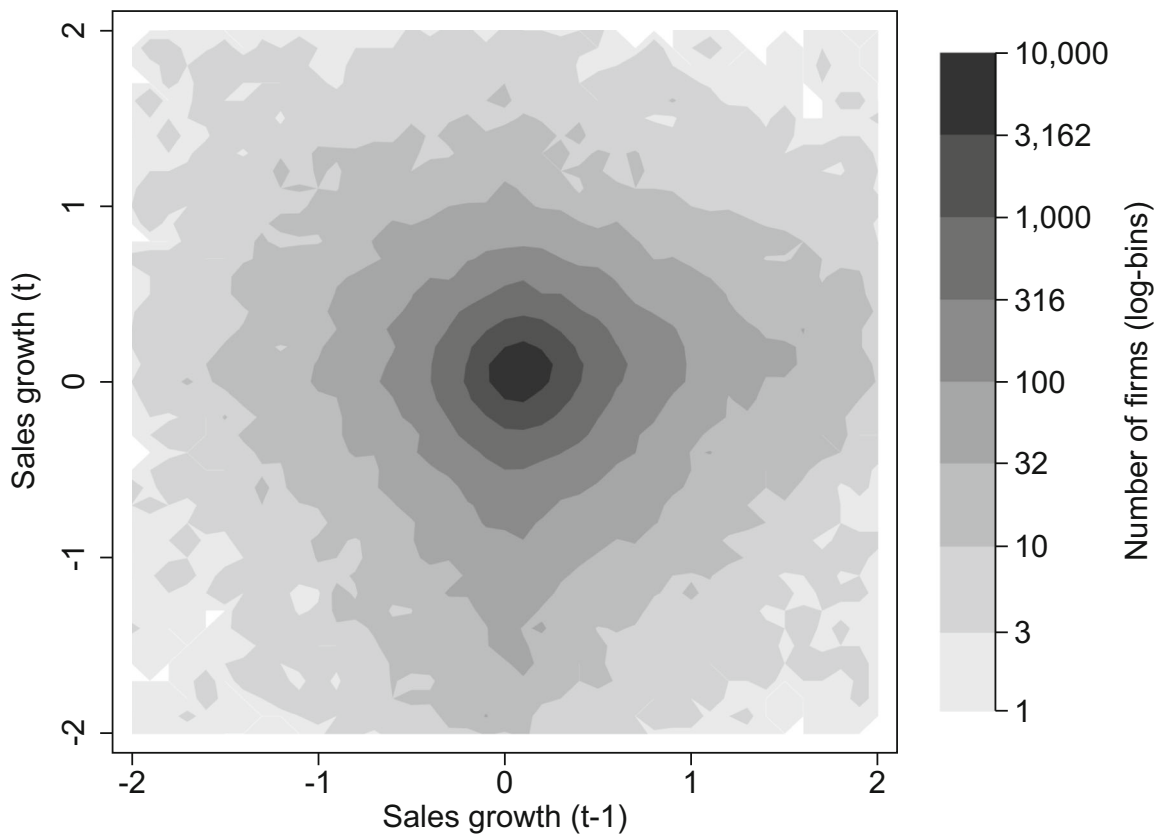

Fig. 4 Contour plot for pairs of consecutive growth rates 2006–2008. Note: *Coloring shades* correspond to the frequency of the number of firms in categorized into logarithmic bins. *White areas* contain no observations without interpolation. The contour is delimited to growth rates ±2
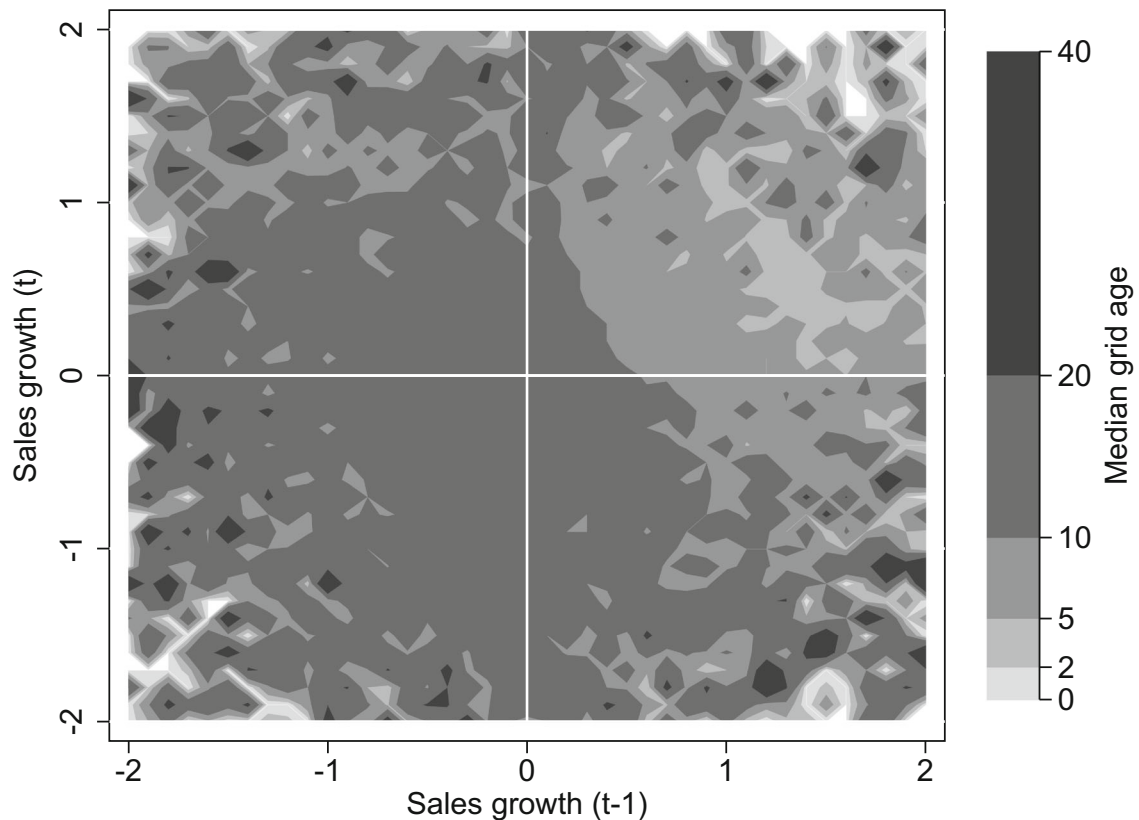
Fig. 5 Contour plot over median grid age for pairs of consecutive growth rates in 2006–2008. Note: Coloring shades corresponds to the four age groups 0–4 years; 5–9 years; 10–19 years; 20–40+, which contains 40+ group. White areas contain no observations without interpolation. The contour is delimited to growth rates ±2
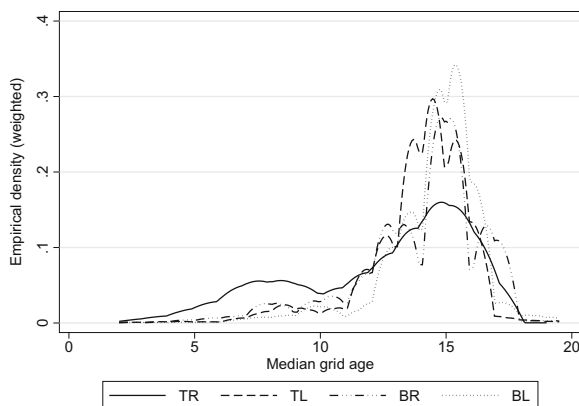

Fig. 6 Empirical density of median ages for the four quadrants in the contour plot (Fig. 5). Note: Analysis of the quadrants in Fig. 5. *TR* top right (positive to positive), *TL* top left (negative to positive), *BR* bottom right (positive to negative), *BL* bottom left (negative to negative). Density plot with an epanechnikov kernel function at 50 points. Pairwise equality of distributions and means are rejected for each pair except for TL and BR by the two-sided Kolmogorov-Smirnov test and the standard *t* test

resources as well as external conditions) affecting the process of growth for the individual firm, the stochastic framework regards those factors as approximately random at the aggregate firm-level. In the cross-sectional analysis of firm growth, the combined effect of these forces amounts to a probability density that describes the dynamic of firm growth (Singh and Whittington 1975). Considering the probability density of growth rates, autocorrelation refers to a type of intra-distributional movement, where the realization of past growth affects the expected future growth rates.

To model the dynamics of firm growth, we opt for a simple regression specification, which reflects the fact that there are no clearly identified variables that are able to explain the majority of variation in growth rates (Geroski 2000; Coad 2009; Denrell et al. 2015). More specifically, we consider an age-augmented version of the growth-rate autocorrelation model used in previous

research (Coad 2007; Coad and Hölzl 2009; Bottazzi et al. 2011), given by

$$growth_{i,t} = \mu + \gamma_s size_{i,t-1} + \gamma_g growth_{i,t-1}$$
$$+ \gamma_a age_{i,t,1} + \epsilon_{i,t}, \qquad (2)$$

In this model, growth is governed by four parameters. The first is the constant term, μ, that captures average yearly growth rates; and the second parameter, γ_s, captures the effect from lagged size. The model is closely related to Gibrat's Law of Proportionate Effect (LPE), which states that growth rates in time t are statistically independent of initial firm size (Gibrat 1931; for overviews, see e.g., Sutton 1997; Caves 1998; Lotti et al. 2003; Gilbert et al. 2006). This condition is usually associated with having $\gamma_s = 0$, which means that there are no effects on growth from lagged size. If the LPE is violated, lagged size either has a positive effect on growth with $\gamma_s < 0$ or a negative effect $\gamma_s < 0$. In the first case ($\gamma_s > 0$), growth becomes explosive as they grow increasingly faster when they become larger. Evidently, this scenario can only be temporary, as we do not observe infinitely large firms, and cannot result in a steady-state distribution for firm size. The other case ($\gamma_s < 0$) means that size regresses to the mean over time and, as a consequence, allows smaller firms to grow faster than already large firms.

The third parameter in the model is γ_g, which refers to the effect from lagged growth rates, i.e., whether growth rates are persistent. We use persistence and autocorrelation in growth rates interchangeably, henceforth. This parameter is also intimately linked to the LPE. Should $|\gamma_g| > 0$, such that growth rates are (auto) correlated, growth can either encourage ($\gamma_g > 0$) or discourage ($\gamma_g < 0$) subsequent growth, which also results in a dependence between firm size and growth (Chesher 1979). Thus, in order for the LPE to apply, the condition $\gamma_g = 0$ also needs to be fulfilled in addition to $\gamma_s = 0$. It is mainly because of this auxiliary condition that growth autocorrelation is considered in the Gibrat literature. While the literature on the LPE is vast, the number of studies that consider growth persistence as a self-contained phenomenon is considerably smaller (see e.g., Daunfeldt and Halvarsson 2015 for a recent survey). The fourth and final parameter γ_a captures the effect from firm age, here measured at the initial period (t-1) of the growth model, which means that the smallest possible age a firm can have in period

t is two. The last term $\epsilon_{i,t}$ is a possibly non-Gaussian disturbance term.

From the basic age-augmented growth-autocorrelation model presented above, we make several extensions. First, and most importantly, we control for industry specific components in growth rates, using our variables for industry entry- and exit-rates, the average industry growth rate, and the Herfindahl concentration ratio. The industry variables are included for year t-1. As a further precaution, we remove firms that went through some form of M&A activity during the period t, t-1, or t-2. We also have information at the firm-level regarding whether a firm belongs to a business group. Along with industry variables, we therefore introduce a dummy that takes the value one if a firm belongs to a business group in t-1, and zero otherwise.

As a second extension, we test whether growth autocorrelation varies with firm age by interacting $growth_{t-1}$ with age_{t-1}. This extended model is able to capture any linear relationships between age and growth autocorrelation. However, should the relationship be non-linear, the interaction term only presents a first approximation. We, therefore, in a third extension, repeat the analysis without the interaction term but restricting the sample to distinct age groups.

Our choice of estimator for Eq. (1) is based on the particularities of the error term (ϵ_{it}), which inherits the particular "tent-shape" that characterize the distribution of firm-growth rates, as seen in Fig. 2. It is well-established that firm growth tends to follow the Laplace distribution (Stanley et al. 1996; Bottazzi and Secchi 2006; Bottazzi et al. 2011), with most firms not growing at all while a few firms grow very fast. Since this violates the normality assumption of $\epsilon_{i,t}$, OLS becomes less attractive, whereas least absolute deviation (LAD) becomes more suitable (Fotopoulos and Louri 2004; Coad and Rao 2008; Reichstein et al. 2010; Bottazzi et al. 2011; Capasso et al. 2014).

Instead of a normal distribution, LAD (also known as median regression) assumes the error terms to be Laplace-distributed. Another advantage comes from its robust estimation in the presence of outliers on the dependent variable that tends to $\pm\infty$, which becomes relevant in the presence of very fast-growing firms. Since these firms' growth rates can distort the mean but not the median, median regression is better suited and more robust

Table 3 Results from median regression on all firms in 2008

Variables (lagged one period)	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Initial growth	0.004***	0.021***	0.021***	0.021***	0.021***	0.021***	0.021***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
ln(sales)	0.002***	0.003***	0.003***	0.003***	0.003***	0.003***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Growth#Age		−0.001***	−0.001***	−0.001***	−0.001***	−0.001***	−0.001***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Industry growth			0.098***	0.104***	0.116***	0.098***	0.098***
			(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Herfindahl index				−0.041***	−0.042***	−0.040***	−0.042***
				(0.010)	(0.007)	(0.009)	(0.009)
Entry Rate					−0.029**	−0.074***	−0.081***
					(0.011)	(0.014)	(0.013)
Exit Rate						−0.197***	−0.226***
						(0.027)	(0.028)
Business grp.							0.009***
							(0.001)
Constant	0.033***	0.028***	0.023***	0.024***	0.027***	0.041***	0.055***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
Observations	157,439	157,439	157,439	157,439	157,439	157,439	157,439
Pseudo R2	0.000956	0.00120	0.00127	0.00133	0.00133	0.00143	0.00152

*$p < 0.10$; ** $p < 0.05$; ***$p < 0.01$

than OLS (Bottazzi et al. 2011). Finally, Eq. (1) is estimated using robust standard errors.[10]

5 Regression results

5.1 Main analysis

The results from the main analysis are presented in Table 3. The first column estimates Eq. (2) without control variables. These results capture the median autocorrelation among firms while controlling for firm age. To test our hypotheses, the second column incorporates an interaction term between age and lagged growth. This variable captures any linear relationship

between firm-age and growth-autocorrelation. In the following columns (3) to (7), we introduce additional

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[10] All median regression estimations are performed in Stata using the *qreg* with the *vce(robust)* option. Bootstrapping our standard errors was not a viable option due to the numerous regressions undertaken at each age.
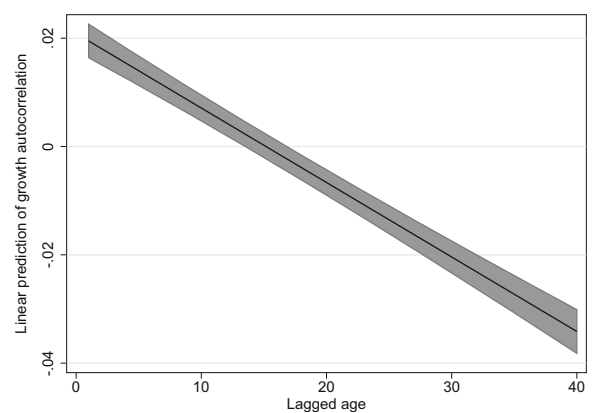

Fig. 7 Average marginal effects of sales growth (t-1) as a linear function of age with 95% CIs. Note: The plot shows the estimated marginal effect on the vertical axis from initial (lagged) growth for firms with ages (lagged) going from 1 to 40, on the horizontal axis

controls variables to see whether industry structure variables account for some variation in firm growth rates.

In the baseline model in column (1), the coefficient on lagged growth, 0.004, is small and positive, but highly significant, indicating that firm growth is overall marked by positive growth-rate autocorrelation.[11] This implies that positive growth rates tend to be followed by more positive growth rates, and that negative growth rates are followed by more negative growth rates. A 1 unit change in median sales growth in period t-1 translates into a 0.4 percentage point (0.004) increase in sales growth in period t. In terms of one standard deviation (0.608 as reported in Table 1) as the unit change, the corresponding increase in sales growth amounts to 0.24 percentage points (0.608*0.004=0.0024). For the median firm with a growth rate of 5.2% (Table 1) at t-1, the latter change predicts a very subtle increase to 5.44%, which in terms of the median growth rate corresponds to a 4.62% (5.44/5.2 − 1) increase. Stated yet another way, the rate at which the median firm grows increased by 4.62% as a consequence of its lagged growth rate.

Gibrat's (1931) prediction that size is independent of growth rates (LPE) can also be rejected. We observe a slightly positive relationship between growth rate and lagged size for the full sample (coefficient = 0.002), whereas firm age is negatively related to firm growth for the full sample (Table 2 column (1)), indicating that older firms have lower expected sales growth rates of 0.1% for each additional year.[12]

The interaction term for age and lagged growth is important for the purposes of testing our hypotheses, but its interpretation needs some explanation. The inclusion of an interaction term in column 2 between lagged growth and firm age changes the estimate of growth autocorrelation to 0.02, up from 0.004. Since we enter firm age in (integer) levels, the direct effect of 0.02 applies to hypothetical firms aged zero years, but as age enters the models with one lag, the youngest firms are 1 year. As the interaction term is negative, it means that growth autocorrelation for firms aged 1 to 40 is predicted to decrease from 0.02 by 0.1% for each for each additional year as the

median firm ages. Since the interaction term postulates a linear relationship between firm age and growth-rate autocorrelation, the model also predicts that autocorrelation is effectively zero for firms of 15 years of age. For older firms, the linear prediction results in negative autocorrelation rates, which for firms aged 40 becomes −0.035. This implies that positive growth rates tend to be followed by more negative growth rates, and that negative growth rates are followed by more positive growth rates. We illustrate this predicted linear relationship in Fig. 7 that plots the autocorrelation rates for firms aged 1 to 40 years together with 95% confidence intervals. Figure 7 shows that the correlation coefficient is estimated to change from significantly positive to zero at around age 15 and to become increasingly negative afterwards. Hence, Fig. 7 shows how the autocorrelation coefficient varies with age, in a way that is not clearly visible from the regression results shown in Table 3.

Table 3 also indicates that the estimates of age and growth persistence are robust to the inclusion of a number of control variables in columns (3) to (7). These control variables provide additional insights into what influences median growth rates beyond the baseline specification of Eq. (2). According to the results from the full model presented in column (7), positive growth rates are more prevalent among firms that are active in growing industries or in industries with low market-concentration rates or low exit and entry rates. These findings indicate that firms who are active in industries with higher competition or less turbulence in the form of firm entries and exits are more likely to increase their growth further when accounting for initial sales growth rates. Finally, firms that belong to a business group are experiencing positive growth rates more often than single-establishment firms.

While the above analysis helps us to investigate any linear relationship between firm age and autocorrelation, it cannot account for non-linear segments in the relationship between autocorrelation and firm age. Our graphical analyses in Figs. 5 and 6 show that positive autocorrelation rates could be detected for young firms (who are more likely to have consecutive positive growth) and older firms (who are slightly more likely to have consecutive negative growth). To complement these earlier plots, and to investigate possible nonlinearities, we take an alternative regression specification that does not include an interaction term for age and autocorrelation, but that estimates the full model specification separately on five different age groups. This allows autocorrelation to vary freely between these subsamples of the age distribution.

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[11] Since we are interested in the effect on growth rates, we consider the marginal effect on $growth_t$ from a unit change in $growth_{t-1}$ instead of the elasticity defined as the percentage effect change on $size_{i,t}/size_{i,t-1}$ from a percentage change in $size_{i,t-1}/size_{i,t-2}$.

[12] Excluding the age variable from the regression doubles the estimated coefficient on initial growth (not reported). Still not a strikingly high level of autocorrelation, but it suggests some form of relationship between the two variables.

Regression results for different age categories are presented in Table 4. Firms that are younger than 5 years[13] show a positive and significant autocorrelation coefficient for the median firm of 0.041, i.e., twice the rate than predicted by the linear trend in Table 3. Computed for a median growth rate of 8.6% for firms younger than 5 years in $t-1$, one standard deviation increase of 0.673 (reported in Table 1) corresponds to a 2.76 percentage points increase $(0.673^*0.041 = 0.276)$ and thus a 32.09% increase $((8.6 + 2.76)/8.6 - 1 = 0.3209)$ in the speed of growth rates in t. Although the autocorrelation rate is twice as high for firms in the youngest age group than predicted in Table 3, the surge in growth rates of 32.09% found here is close to the prediction of 26.15%, which gives credence to the linear specification in Table 3 for the youngest firms.

We also observe from column 2 in Table 4 that autocorrelation turns negative for firms that are 5–9 years, rather than at the intercept of 15 years as predicted by the linear specification (implicit in Table 3 and emphasized in Fig. 7). Autocorrelation thereafter turns significant and increasingly more negative for firm in age groups 10–19 years and 20–39 years and finally becomes insignificant for firms that are aged 40+. Although the regression analysis does not support a strong U-shaped relationship in autocorrelation rates between firms across the age distribution (which was hinted at by the contour plots), the results in Table 4 at least contradict the strong negative autocorrelation rate that was predicted in Table 3 (and Fig. 7) for older firms.

The results presented in Table 4 also indicate that firm size has a different effect on growth persistence for young firms than for older firms. LPE for all age groups except for firms aged 5 to 9 years, for which autocorrelation is non-significant. For the youngest firms, the LPE is violated because smaller firms grow faster than larger firms, while for firms older than 9 years LPE is violated because larger firms within age groups grow faster than smaller firms. The results by age groups also indicate different results for the control variables. Noteworthy is that the negative results for the Herfindahl index only enter significantly for firms in the age groups 10–19 years and 20–39 years. Thus, for the youngest and oldest firms, competition (as captured by the level of concentration in the industry) does not factor into their growth rates. Also striking is the negative effect observed for turbulence in

terms of the entry and exit rate in columns (1) to (4). It is only the oldest firms that grow faster in industries with a higher entry rate, and growth does not seem to respond to the industry's exit rate.

As a final step in the analysis, we dispense with age groups altogether to investigate the autocorrelation rate for each individual age. Instead of showing a regression table with 39 columns, we present the regression coefficients graphically. Figure 8 plots the median regression estimate of the autocorrelation coefficient on the vertical axis, together with each coefficient's 95% confidence intervals, while age is plotted on the horizontal axis. The figure is based on 39 data points (firms ages 2–40) obtained from 39 cross-sectional regressions (one per year) of the full model (excluding the interaction term). Figure 8 complements the results in Tables 3 and 4. Growth autocorrelation is positive and significant for start-ups with age 2–4 years, but turns insignificant shortly afterwards, and remains negative and significant until about age 17 years, after which it alternates between insignificant and significant, but never turns significantly positive again for older firms.

5.2 Robustness checks

5.2.1 Repeating the analysis for different years

In order to investigate if our results are driven by year-specific effects, we re-estimate all models for each year during the study period (2000–2008) and the results are briefly summarized here.[14] We begin by estimating the series of regressions that form the basis of Fig. 7 for the preferred sample of firms in all years 2000–2007. For every year of the period, young firms "burst into life" with positive growth autocorrelation in their first observable year.[15] In the years after entry, autocorrelation turns insignificant and then significantly negative. When this happens, and for how long autocorrelation stays negative, differs slightly between years.[16] The average period, however, with sustained negative

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[13] Strictly speaking younger than 5 years are firms between 2 and 4 years old since the youngest firm with at least two observed consecutive growth rates is 2 years old (counted as 0 in 2006 when it was founded).

[14] All results are available from the authors upon request.

[15] In 2008, we observed in Figure 3 that the growth dynamic of young firms between 2 and 4 years were characterized by positive autocorrelation. Following the peak of dot-com crises in 2001, positive autocorrelation could only be observed for firms of 2 years. For every other year, positive autocorrelation rates were observed for the median firm the first 2 or 3 years in its life.

[16] For 2008 autocorrelation turned negative and significant for firms of 16 years and remained negative until firms aged 21 years, but for 2002, the negative period took place between ages 9 and 13.

Table 4 Results from median regression on firms divided by age group

Variables (lagged one period)	(1) 0–4 year	(2) 5–9 year	(3) 10–19 years	(4) 20–39 year	(5) 40+ years
Initial growth	0.041***	0.002	−0.014***	−0.023***	−0.005
	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)
ln(sales)	−0.013***	−0.001	0.002***	0.004***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Industry growth	0.244***	0.099***	−0.010	0.090***	0.068
	(0.049)	(0.034)	(0.025)	(0.029)	(0.050)
Herfindahl index	−0.020	−0.015	−0.058***	−0.057***	−0.033
	(0.028)	(0.020)	(0.013)	(0.020)	(0.034)
Entry rate	−0.264***	−0.140***	−0.172***	−0.073**	0.092**
	(0.041)	(0.036)	(0.025)	(0.036)	(0.037)
Exit rate	−0.200**	−0.192***	−0.365***	−0.161***	0.090
	(0.088)	(0.064)	(0.046)	(0.058)	(0.080)
Business group	0.014***	0.003	0.008***	0.011***	0.014***
	(0.005)	(0.003)	(0.002)	(0.003)	(0.004)
Constant	0.265***	0.091***	0.055***	−0.002	−0.012
	(0.017)	(0.011)	(0.008)	(0.009)	(0.012)
Observations	22,324	33,250	57,765	34,710	9390
Pseudo R2	0.00369	0.000209	0.000820	0.00134	0.00174

*$p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

growth rates across all years was found to be roughly between 10 to 17 years. Based on the year-by-year analysis of the non-linear relationship between autocorrelation rates and firm age, we confirm Hypothesis 1b of positive growth autocorrelation for the youngest firms,
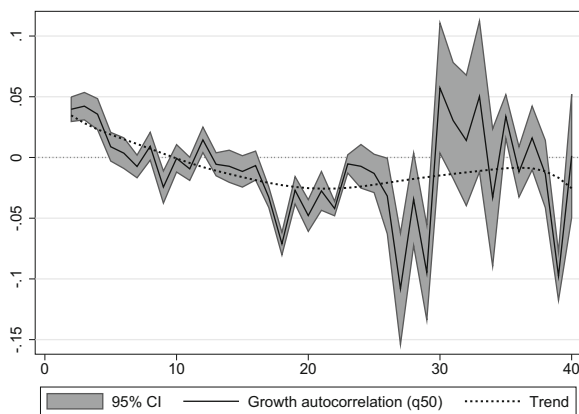

Fig. 8 Estimate of growth autocorrelation (γ_g) from separate median regressions for ages 2–40. The figure is thus based on 39 estimated coefficients with 95%-CIs obtained from the regressions

and we cannot rule out that hypothesis 2a (no autocorrelation) holds for firms older than 20 years.

5.2.2 Selection bias from surviving firms

One possible explanation for our finding of positive autocorrelation in the early years relates to selection effects. More specifically, there might be a "shadow of death" effect, such that some short-lived firms experience two successive periods of decline (hence, positively-correlated growth across years) immediately before exiting. A contrasting explanation would be that our finding of positive growth autocorrelation in the early years could be due to internal developmental factors of firms, for example if young firms (that will survive a long time) struggle to grow in their early years (e.g., to reach a minimum efficient scale of production), and after this initial growth spurt their growth stabilizes as they reach a "steady-state" scale of operation or "optimal size."[17] Ideally, we would investigate selection

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[17] Note however that notions of an "optimal size" for firms have been repeatedly rejected in the empirical literature (Coad 2009, pp100–101).

effects by tracking cohorts of firms for 40 years, conditional on knowing that they will survive for the 40-year period—but this is not possible because our data does not track firms for that long. Instead, the approach we take is to focus on firms that we know will survive several years into the future, thus eliminating observations from short-lived firms that might contribute to a "shadow of death" effect. More specifically, we measure the growth rate autocorrelation of firms of different ages, where the dependent variable is the annual growth rate measured into 2000 to 2004, and inclusion in the sample is conditional on survival into 2009.

The results are available upon request. Similar to our previous results in Fig. 7, we see that growth rate autocorrelation is positive in the first few years after start-up and decreases relatively slowly in the post-entry years, before again stabilizing at a level of negative growth rate autocorrelation until turning insignificant for the older firms. The initial growth spurt is qualitatively similar, and we can confirm that our main analysis is not driven by "shadow of death" selection effects, but instead that the observed patterns in growth rate autocorrelation over age relate to internal developmental factors in firms.

5.2.3 Disaggregating by firm size

One concern is that a large number of one-person firms (also known as solo self-employed individuals) might have been driving our results. We therefore excluded firms that started with one person employed in the period $t-1$ or $t-2$ and repeated the analysis. The initial growth spurt remains and becomes more emphasized when excluding firms of less than or equal to 1 and persists for firms as old as 8 years. After the initial growth spurt, the autocorrelation coefficient turns insignificant and remains insignificant for most older firms, in contrast to a pronounced period of negative and significant coefficients for middle-aged firms (as found in the main analysis).

It is clear that the initial growth spurt reflected in the aggregate is not exclusively a function of the smallest firms, but rather reflects firms of a larger size. This tendency is also confirmed if we estimate

the full model for firms in three different size groups with average number of employees less than 5, 5 to 9, and 10 and above (Table 5). Descriptive statistics for growth rates in these size groups over the age groups is reported in Table 6 in the appendix. The regression results are in Table 7, which clearly shows that autocorrelation is negative for the smallest firms, and therefore suggests that the *positive* autocorrelation for young firms is not being driven by small firms.

5.2.4 Autocorrelation with a second lag

We also extend the model in Eq. (2) to allow for the case where longer lags of growth have an impact on current growth. More specifically, we repeat the analysis in Table 4 with a second growth lag (results available upon request). The results for the first lag are similar to what was observed before. The second lag is often significant and is generally of the same sign as the first lag (although the effect is smaller in magnitude). Overall, adding a second lag yields some interesting results, although a drawback is that we lose a year of observation (which is particularly problematic given our focus on the years immediately after entry).

6 Summary and conclusions

Firm age has been argued to be one of the most important determinants of firm growth (Fizaine 1968; Haltiwanger et al. 2013; Lawless 2014). However, we still know very little about how growth patterns change with age. The lack of studies can most likely be explained by the absence of data on firm age and the under-representation of young firms in many available longitudinal datasets. We overcome these shortcomings by using a dataset that includes information on the years since registration of all Swedish limited liability firms of all sizes.

While previous literature has investigated how growth varies with age, or how growth varies with previous growth, our contribution is to examine

how growth autocorrelation varies with age. A coherent story emerges from a range of non-parametric and parametric techniques, that provide a rich, coherent and novel set of results regarding how growth patterns change with age. Our results indicate that young firms are characterized by positive autocorrelation in growth rates, suggesting that growth in one period is positively related to growth in the next. Positive autocorrelation in the growth of young firms is observed alongside a higher mean and standard deviation of the growth rates distribution for young firms. Graphical analyses, accompanied by statistical tests, reveal that young firms are more likely to experience positive growth in two successive periods. Older firms are less likely to experience two periods of positive growth, and very old firms are more likely to experience two successive periods of *negative* growth.

Sales growth autocorrelation turns negative in the years after entry. New firms strive to grow in order to achieve a minimum efficient scale and overcome their "liability of newness" (Cabral 1995), but once they have survived the first few years it seems that their growth loses its momentum. We thus found no support for notions that older firms should have a high degree of growth persistence due to learning effects, well-established capabilities, or from operating with longer strategic time horizons. Instead, the growth of mature firms would be better characterized by theoretical models that predict negative autocorrelation, for example if investment is lumpy, if firms' resources are discrete, and if growth in one period is unlikely to be followed by growth in the following period (Coad and Planck 2012). Furthermore, our findings on the erratic growth of older firms can be related to theories of the liabilities of aging (Barron et al. 1994): i.e., the liability of senescence (i.e., how accumulated rules, routines and structures lead to organizational ossification and structural rigidity) and the liability of obsolescence (regarding the organization's fit to the environmental context). Hence, older firms who suffer from liabilities of senescence and obsolescence might be more vulnerable to setbacks in their growth trajectories, as these rigid old organizations are buffeted around in ever-changing environments.

Our analysis does not come without limitations. One question is whether our results can potentially be generalized to other contexts and countries. We believe that this is likely since Coad et al. (2013b) reported similar results for Spain, although their study was vulnerable to selection bias due to data limitations, and the relationship between growth autocorrelation and age was not explored in much depth. Nevertheless, we would welcome further investigations in other contexts.

Future work could investigate more closely which specific mechanisms account for the positive growth autocorrelation among young firms. One explanation might relate to the legitimacy that young firms accumulate, due to the increasing returns to customer adoption that arises when the customer base grows rapidly before reaching satiation. Another explanation could be the increasing returns that arise from gains to routinization, as employee attention is freed up and productivity improves.

Further research could also investigate in more detail the patterns of growth for young firms and whether it differs among start-ups. One particularly interesting question is whether young firms should first seek profits, or first seek growth. Davidsson et al. (2009), for example, presented evidence that profitable firms are more likely to attain high profits and high growth in the future compared to those firms that seek growth before profits. Our findings might, however, indicate that young firms should first seek to grow, because there are positive feedback effects of early growth on subsequent growth, as well as other possible benefits such as survival benefits (Phillips and Kirchhoff 1989; Coad et al. 2013a) that come from growth per se and from the larger size that this begets.

Appendix

Table 5 Description of sales growth by age categories for three different employment-size categories (2008)

Empl. < 5	Obs	Mean	Stdev	Min	Q25	Median	Q75	Max
0–4 year	17,166	0.064	0.717	−8.674	−0.116	0.083	0.286	6.764
5–9 year	22,997	0.026	0.691	−7.801	−0.146	0.055	0.234	6.907
10–19 years	39,727	−0.008	0.673	−8.196	−0.145	0.039	0.192	7.762
20–39 year	21,556	−0.032	0.644	−7.823	−0.159	0.024	0.162	7.594
40+ years	4209	−0.048	0.649	−7.048	−0.141	0.024	0.137	7.209
All firms	105,655	0.005	0.678	−8.674	−0.144	0.044	0.207	7.762
Empl. 5 < 10	Obs	Mean	Stdev	Min	Q25	Median	Q75	Max
0–4 year	3185	0.076	0.503	−5.925	−0.034	0.095	0.247	4.377
5–9 year	5734	0.038	0.455	−8.249	−0.056	0.073	0.192	4.136
10–19 years	9378	0.004	0.467	−9.755	−0.066	0.056	0.158	5.920
20–39 year	6280	0.008	0.397	−8.552	−0.063	0.048	0.140	5.117
40+ years	1607	−0.011	0.397	−4.236	−0.068	0.040	0.127	2.394
All firms	26,184	0.020	0.450	−9.755	−0.061	0.060	0.167	5.920
Empl. > 10	Obs	Mean	Stdev	Min	Q25	Median	Q75	Max
0–4 year	1973	0.087	0.481	−3.643	−0.032	0.089	0.243	5.927
5–9 year	4519	0.067	0.412	−5.277	−0.029	0.084	0.197	8.688
10–19 years	8660	0.034	0.424	−8.198	−0.039	0.071	0.167	4.022
20–39 year	6874	0.025	0.378	−7.108	−0.043	0.060	0.148	7.167
40+ years	3574	0.017	0.364	−7.224	−0.045	0.049	0.127	3.440
All firms	25,600	0.039	0.407	−8.198	−0.039	0.068	0.165	8.688

Table 6 Description of average size in terms of number of employees by the preferred sample of firms across age categories in 2008

All firms	Obs	Mean	Stdev	Min[a]	Q25	Median	Q75	Max
0–4 year	22,324	5.147	32.233	0	1.000	2.000	4.500	3509
5–9 year	33,250	7.607	48.841	0	1.000	2.500	6.000	3828
10–19 years	57,765	8.929	107.340	0	1.000	2.500	6.000	19,690
20–39 year	34,710	12.104	116.525	0	1.500	3.000	7.500	13,711
40+ years	9390	48.461	365.487	0	2.000	6.000	19.000	18,297
All firms	157,439	11.171	126.218	0	1.000	3.000	6.500	19,690

[a] Average size for 2008 is computed as the average size between the periods t-1 and t-2, which for 2008 means 2007 and 2006. Although firms with zero employees (at 2008) are excluded from the sample, the minimum of average firm size can still report zero average size. This is because average age is computed for firms in year *t-1* and *t-2*, and to avoid restricting the sample more than necessary, we choose to drop the non-zero restriction for 2006 and 2007. This amount to about 1% of the firms that all have at least one employee in 2008, but 0 employees the years 2006 and 2007

Table 7 Results from median regression on firms divided by size group

Variables (lagged one period)	(1) <5 Empl	(2) 5–9 Empl	(3) 10+ Empl
Growth	−0.001	0.053***	0.037***
	(0.001)	(0.002)	(0.002)
ln(sales)	−0.017***	−0.003*	0.000
	(0.001)	(0.001)	(0.001)
Age	−0.001***	−0.001***	−0.000***
	(0.000)	(0.000)	(0.000)
Industry growth	0.089***	0.039	−0.058*
	(0.023)	(0.036)	(0.033)
Herfindahl index	−0.083***	0.004	0.015
	(0.012)	(0.022)	(0.013)
Entry Rate	−0.169***	−0.024	0.124***
	(0.021)	(0.034)	(0.027)
Exit Rate	−0.404***	−0.107*	0.055
	(0.038)	(0.061)	(0.049)
Business group	0.019***	−0.005**	−0.005**
	(0.002)	(0.003)	(0.002)
Constant	0.297***	0.109***	0.066***
	(0.008)	(0.021)	(0.010)
Observations	105,655	26,184	25,600
Pseudo R2	0.00304	0.00431	0.00370

*$p < 0.10$; ** $p < 0.05$; ***$p < 0.01$

References

Almus, M., & Nerlinger, E. (2000). Testing "Gibrat's law" for young firms—empirical results for West Germany. *Small Business Economics, 15*(1), 1–12. doi:10.1023/a:1026512005921.

Anyadike-Danes M., Hart M. (2014). All grown up? The fate after 15 years of the quarter of a million UK firms born in 1998. Sept 14th, Mimeo.

Arrow, K. J. (1962). The economic implications of learning by doing. *Review of Economic Studies, 29*, 155–173. doi:10.1007/978-1-349-15430-2_11.

Audretsch, D. B. (1995). Innovation, growth and survival. *International Journal of Industrial Organization, 13*, 441–457. doi:10.1016/0167-7187(95)00499-8.

Bamford, C. E., Dean, T. J., & Douglas, T. J. (2004). The temporal nature of growth determinants in new bank foundings: Implications for new venture research design. *Journal of Business Venturing, 19*, 899–919. doi:10.1016/j.jbusvent.2003.05.001.

Barba Navaretti, G., Castellani, D., & Pieri, F. (2014). Age and firm growth: evidence from three European countries. *Small Business Economics, 43*(4), 823–837. doi:10.1007/s11187-014-9564-6.

Barron, D. N., West, E., & Hannan, M. T. (1994). A time to grow and a time to die: growth and mortality of credit unions in New York, 1914-1990. *American Journal of Sociology, 100*(2), 381–421. doi:10.1086/230541.

Bettis, R., Gambardella, A., Helfat, C., & Mitchell, W. (2014). Quantitative empirical analysis in strategic management. *Strategic Management Journal, 35*(7), 949–953. doi:10.1002/smj.2278.

Bianchini, S., Bottazzi, G., & Tamagni, F. (2016). What does (not) characterize persistent corporate high-growth? *Small Business Economics, 48*(3), 633–656 doi:10.1007/s11187-016-9790-1.

Bottazzi, G., & Secchi, A. (2006). Explaining the distribution of firm growth rates. *RAND Journal of Economics, 37*(2), 235–256. doi:10.1111/j.1756-2171.2006.tb00014.x.

Bottazzi, G., Coad, A., Jacoby, N., & Secchi, A. (2011). Corporate growth and industrial dynamics: evidence from French manufacturing. *Applied Economics, 43*(1), 103–116. doi:10.1080/00036840802400454.

Cabral, L. (1995). Sunk costs, firm size and firm growth. *Journal of Industrial Economics, 43*(2), 161–172. doi:10.2307/2950479.

Capasso, M., Cefis, E., & Frenken, K. (2014). On the existence of persistently outperforming firms. *Industrial and Corporate Change, 23*(4), 997–1036. doi:10.1093/icc/dtt034.

Caves, R. E. (1998). Industrial organization and new findings on the turnover and mobility of firms. *Journal of Economic Literature, 36*(4), 1947–1982 http://www.jstor.org/stable/2565044.

Chang, Y., Gomes, J. F., & Schorfheide, F. (2002). Learning-by-doing as a propagation mechanism. *American Economic Review, 92*, 1498–1520. doi:10.2139/ssrn.277131.

Chesher, A. (1979). Testing the law of proportionate effect. *Journal of Industrial Economics, 27*(4), 403–411.

Coad, A. (2007). A closer look at serial growth rate correlation. *Review of Industrial Organization, 31*, 69–82. doi:10.1007/s11151-007-9135-y.

Coad A., (2009). The growth of firms: a survey of theories and empirical evidence. Edward Elgar, Cheltenham, UK and Northampton, MA, USA.

Coad, A, & Planck, M. (2012). Firms as bundles of discrete resources – towards an explanation of the exponential distribution of firm growth rates. *Eastern Economic Journal, 38*, 189–209.

Coad, A. (2017). Firm age: a survey. *Journal of Evolutionary Economics, forthcoming.* doi:10.1007/s00191-016-0486-0.

Coad, A., & Hölzl, W. (2009). On the autocorrelation of growth rates. *Journal of Industry Competition and Trade, 9*(2), 139–166. doi:10.1007/s10842-009-0048-3.

Coad, A., & Rao, R. (2008). Innovation and firm growth in high-tech sectors: a quantile regression approach. *Research Policy, 37*(4), 633–648. doi:10.1016/j.respol.2008.01.003.

Coad, A., Frankish, J., Roberts, R., & Storey, D. (2013a). Growth paths and survival chances: an application of Gambler's ruin theory. *Journal of Business Venturing, 28*, 615–632. doi:10.1016/j.jbusvent.2012.06.002.

Coad, A., Segarra, A., & Teruel, M. (2013b). Like milk or wine: does firm performance improve with age? *Structural Change and Economic Dynamics, 24*, 173–189. doi:10.2139/ssrn.1815028.

Coad, A., Daunfeldt, S.-O., Hölzl, W., Johansson, D., & Nightingale, P. (2014). High-growth firms: Introduction to a special issue. *Industrial and Corporate Change, 23*, 91–112. doi:10.1093/icc/dtt052.

Coad, A., Frankish, J. S., Roberts, R. G., & Storey, D. J. (2016). Predicting new venture survival and growth: does the fog lift? *Small Business Economics, 47*, 217–241. doi:10.2139/ssrn.2408027.

Collier, B. L., Haughwout, A. F., Kunreuther, H. C., Michel-Kerjan, E. O., & Stewart, M. A. (2016). Firm age and size and the financial management of infrequent shocks (No. w22612). National Bureau of Economic Research.

Daunfeldt, S.-O., & Halvarsson, D. (2015). Are high-growth firms one hit wonders? Evidence from Sweden. *Small Business Economics, 44*(2), 361–383. doi:10.1007/s11187-014-9599-8.

Daunfeldt, S.-O., Elert, N., & Johansson, D. (2014). Economic contribution of high-growth firms: do policy implications depend on the choice of growth indicator? *Journal of Industry, Competition and Trade, 14*, 337–365. doi:10.1007/s10842-013-0168-7.

Davidsson, P., Steffens, P., & Fitzsimmons, J. (2009). Growing profitable or growing from profits: putting the horse in front of the cart? *Journal of Business Venturing, 24*(4), 388–406. doi:10.4337/9780857933614.00017.

Decker, R., Haltiwanger, J., Jarmin, R., & Miranda, J. (2014). The role of entrepreneurship in US job creation and economic dynamism. *Journal of Economic Perspectives, 28*(3), 3–24. doi:10.1257/jep.28.3.3.

Delmar, F. (1997). 'Measuring growth: methodological considerations and empirical results'. In R. Donckels, A. Miettinen (Eds.), *Entrepreneurship and SME research: on its way to the next millennium*, (pp. 190–216). Aldershot, VA: Avebury

Delmar, F., Davidsson, P., & Gartner, W. B. (2003). Arriving at the high-growth firm. *Journal of Business Venturing, 18*, 189–216. doi:10.4337/9781781009949.00018.

Denrell, J., Fang, C., Liu, C., (2015). Chance explanations in the management sciences. Organization Science, in press.

Dunne, P., & Hughes, A. (1994). Age, size, growth and survival: UK companies in the 1980s. *Journal of Industrial Economics 42*(2), 115–140.

Dunne, T., Roberts, M., & Samuelson, L. (1989). The growth and failure of US manufacturing plants. *Quarterly Journal of Economics, 104*(4), 671–698. doi:10.2307/2937862.

Evans, D. S. (1987). The relationship between firm growth, size and age: estimates for 100 manufacturing industries. *Journal of Industrial Economics, 35*, 567–581. doi:10.2307/2098588.

Fizaine, F. (1968). Analyse statistique de la croissance des entreprises selon l'âge et la taille. *Revue d'économie Politique, 78*, 606–620.

Folta, T. B., Delmar, F., & Wennberg, K. (2010). Hybrid entrepreneurship. *Management Science, 56*(2), 253–269. doi:10.1287/mnsc.1090.1094.

Fotopoulos, G., & Louri, H. (2004). Firm growth and FDI: Are multinationals stimulating local industrial development? *Journal of Industry, Competition and Trade, 4*(3), 163–189. doi:10.1023/b:jict.0000047300.88236.f1.

Garnsey, E. (1998). A theory of the early growth of the firm. *Industrial and Corporate Change, 7*(3), 523–556. doi:10.1093/icc/7.3.523.

Garnsey, E., & Heffernan, P. (2005). Growth setbacks in new firms. *Futures, 37*(7), 675–697. doi:10.2139/ssrn.1923138.

Geroski, P. A. (2000). The growth of firms in theory and in practice. In N. Foss & V. Mahnke (Eds.), *Competence, governance and entrepreneurship* (pp. 168–186). Oxford: Oxford University Press.

Gibrat, R. (1931). *Les inégalités économiques*. Paris: Librairie du Receuil Sirey.

Gilbert, B. A., McDougall, P. P., & Audretsch, D. B. (2006). New venture growth: a review and extension. *Journal of Management, 32*(6), 926–950. doi:10.1177/0149206306293860.

Goddard, J., Wilson, J., & Blandon, P. (2002). Panel tests of Gibrat's law for Japanese manufacturing. *International Journal of Industrial Organization, 20*, 415–433.

Greiner, L. E. (1998). *Evolution and revolution as organizations grow* (pp. 55–67). Harvard Business Review. doi:10.1016/s0167-7187(00)00085-0.

Haltiwanger, J., Jarmin, R. S., & Miranda, J. (2013). Who creates jobs? Small versus large versus young. *Review of Economics and Statistics, 95*(2), 347–361. doi:10.1162/rest_a_00288.

Headd, B., & Kirchhoff, B. (2009). The growth, decline and survival of small businesses: an exploratory study of life cycles. *Journal of Small Business Management, 47*(4), 531–550. doi:10.1111/j.1540-627x.2009.00282.x.

Helfat, C. E. (2007). Stylized facts, empirical research and theory development in management. *Strategic Organization, 5*(2), 185–192. doi:10.1177/1476127007077559.

Hölzl, W. (2014). Persistence, survival, and growth: a closer look at 20 years of fast-growing firms in Austria. *Industrial and Corporate Change, 23*(1), 199–231.

Huergo, E., & Jaumandreu, J. (2004). How does probability of innovation change with firm age? *Small Business Economics, 22*, 193–207. doi:10.1023/b:sbej.0000022220.07366.b5.

Ijiri, Y., & Simon, H. A. (1967). A model of business firm growth. *Econometrica, 35*(2), 348–355.

Lawless, M. (2014). Age or size? Contributions to job creation. *Small Business Economics, 42*, 815–830. doi:10.1007/s11187-013-9513-9.

Levinthal, D. A. (1991). Random walks and organizational mortality. *Administrative Science Quarterly, 36*(3), 397–420. doi:10.2307/2393202.

Lotti, F., Santarelli, E., & Vivarelli, M. (2003). Does Gibrat's law hold among young, small firms? *Journal of Evolutionary Economics, 13*(3), 213–235. doi:10.1007/s00191-003-0153-0.

Lotti, F., Santarelli, E., & Vivarelli, M. (2009). Defending Gibrat's law as a long-run regularity. *Small Business Economics, 32*, 31–44. doi:10.1007/s11187-007-9071-0.

McKelvie, A., & Wiklund, J. (2010). Advancing firm growth research: a focus on growth mode instead of growth rate. *Entrepreneurship Theory and Practice, 34*(2), 261–288. doi:10.4337/9780857933614.00014.

Parker, S. C. (2004). *The economics of self-employment and entrepreneurship*. Cambridge University Press.

Parker, S. C., Storey, D. J., & van Witteloostuijn, A. (2010). What happens to gazelles? The importance of dynamic management strategy. *Small Business Economics, 35*, 203–226. doi:10.1007/s11187-009-9250-2.

Phillips, B. D., & Kirchhoff, B. A. (1989). Formation, growth and survival; small firm dynamics in the US economy. *Small Business Economics, 1*, 65–74. doi:10.1007/bf00389917.

Reichstein, T., Dahl, M. S., Ebersberger, B., & Jensen, M. B. (2010). The devil dwells in the tails: a quantile regression approach to firm growth. *Journal of Evolutionary Economics, 20*(2), 219–231. doi:10.1007/s00191-009-0152-x.

Robson, P., & Bennett, R. (2000). SME growth: the relationship with business advice and external collaboration. *Small Business Economics, 15*(3), 193–208. doi:10.1023/a:1008129012953.

Shepherd, D., & Wiklund, J. (2009). Are we comparing apples with apples or apples with oranges? Appropriateness of knowledge accumulation across growth studies. *Entrepreneurship Theory and Practice, 33*(1), 105–123. doi:10.4337/9780857933614.00013.

Singh, A., & Whittington, G. (1975). The size and growth of firms. *Review of Economic Studies, 42*(1), 15–26.

Sorensen, J. B., & Stuart, T. E. (2000). Aging, obsolescence, and organizational innovation. *Administrative Science Quarterly, 45*, 81–112. doi:10.2307/2666980.

Stanley, M. H. R., Amaral, L. A. N., Buldyrev, S. V., Havlin, S., Leschhorn, H., Maass, P., Salinger, M. A., & Stanley, H. E. (1996). Scaling behavior in the growth of companies. *Nature, 379*, 804–806. doi:10.1038/379804a0.

Stinchcombe, A. (1965). Social structure and organizations. In J. G. March (Ed.), *Handbook of organizations* (pp. 142–193). Chicago: Rand McNally.

Sutton, J. (1997). Gibrat's legacy. *Journal of Economic Literature, 35*(1), 40–59 http://www.jstor.org/stable/2729692.

Tornqvist, L., Vartia, P., & Vartia, Y. O. (1985). How should relative changes be measured? *American Statistician, 39*(1), 43–46. doi:10.2307/2683905.

Yasuda, T. (2005). Firm growth, size, age and behaviour in Japanese manufacturing. *Small Business Economics, 24*(1), 1–15. doi:10.1007/s11187-005-7568-y.