RATIO

Ratio Working Paper No. 264

BURSTING INTO LIFE: FIRM GROWTH AND PERSISTENCE BY AGE

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ACKNOWLEDGEMENTS: We would like to thank Martin Carree, Marc Cowling, Michaela Niefert, and seminar participants at Södertörn University as well as participants at ZEW (Mannheim), the 2014 Babson College Entrepreneurship Research Conference (London, Ontario) for valuable comments Any remaining errors are ours alone.

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ABSTRACT

Is firm growth more persistent for young or old firms? Theory gives us no clear answer, 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 1997-2010, covering firms of all ages and information on registered start year. We find that sales growth for new ventures is characterized by positive persistence, whereas it quickly turns negative and remains negative as firms get older. It thus seems that the growth paths of older firms are buffeted around by environmental turbulence, and that older firms may have challenges in adapting their strategies to changing market conditions, whereas new firms experience an early burst of sustained growth.

Keywords: Firm age; growth rate autocorrelation; sales growth; learning-by-doing; minimum efficient scale

JEL-codes: D22; L25; L26

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 characteristics 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 limited 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 information 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 regularities 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 liability firms during 1997-2010. 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, 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.

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

Coad et al. (2013b) 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 fewer than five years, until persistence becomes negative. This 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. THEORETICAL BACKGROUND

Theory has suggested that young firms have higher average growth rates as they grow in the years after entry, because they struggle to overcome their 'liability of newness' (Stinchcombe, 1965) and also their liability of smallness, in order to quickly reach a larger, more efficient scale of operation (close to, or above, the 'Minimum Efficient Scale'). However, 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 one 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 negative autocorrelation in growth rates for young firms.

Older firms, in contrast, will 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). Learning-by-doing models (Arrow, 1962; Sorensen and Stuart, 2000; Chang et al., 2002) 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 escaped attention, nevertheless the evidence on how growth persistence varies with size suggests that larger firms have smoother growth profiles than smaller firms.[2] To the extent that age and size are closely related (e.g. Greiner, 1972), we might also expect that older firms will have positive growth rate autocorrelation, while that for younger firms might be negative.

An alternative view, however, would be that older firms 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 contrast, young firms might seek to achieve a 'minimum efficient scale' (MES) as they struggle to overcome their 'liability of newness' and achieve economies of scale (Lotti et al., 2009). However, once they have survived the first few years and have settled into their new organizational routines, their growth will lose its momentum.

The theoretical literature, discussed above, therefore makes conflicting predictions regarding how the persistence of growth (and therefore growth rate autocorrelation) varies with firm age. Our discussion of the available theory was presented to help

[2] A number of studies have previously analyzed the persistence of firm growth. 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., 2002a). Coad (2007), Coad and Hölzl (2009) and Capasso et al. (2014) have attempted to untangle 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.'

motivate interest in our research question, and to highlight the controversies surrounding the issue, as well as the lack of theoretical guidance, rather than to lead us to elaborate a set of specific hypotheses. Given the conflicting theoretical predictions, as well as the exploratory nature of our fact-finding empirical analysis, we prefer not to formulate precise hypotheses at this stage (closely following the recommendations in Helfat, 2007), but instead ask the reader to keep these theoretical concepts in mind as we examine the empirical evidence.

3. DATA

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 data-sets 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, gathers 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). 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. In addition, the data include all variables that can be found in the annual reports, e.g., number of employees, sales, profits, and liquidity.

We restrict our analysis to active firms ($i = 1, \dots, n$), 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.

$$growth_{i,t} = \log\ (size_{i,t}) - \log(size_{i,t-1}),$$

where

[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).

$$size_{i,t} = sales_{i,t}/\overline{sales}_{j,t}$$

Firm size is measured using sales divided by average industry size, in order to remove any spurious industry effects and to control for possible industry-specific common components of sales growth.[4] Average industry size ($j = 1, \ldots, m$) is computed at the NACE rev.1 three-digit level.[5] Additionally, all sales values have been corrected for inflation.

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. We have also performed all analyses with employment as growth indicator: the results are similar and are discussed later on. This indicates that the results are not particular sensitive to which of these growth indicators are chosen, confirming findings from Daunfeldt et al. (2014).

Our main variable of interest is firm age, which is defined as the observation year minus the registered start year. Except for the hump around age 20 and 40 the distribution appears to show exponential decay.[6] Compared to other studies on firm age, we do not need to work with truncated or 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. The age distribution of firms in 2010 is presented in Figure 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 three years (Coad et al., 2013a; Anyadike-Danes and Hart, 2014).

[Figure 1 about here]

The mean age in 1997 is 13.6 (median = 9 years) and the corresponding mean in 2010 is 14.2 (median = 10 years), showing no large differences in the central tendency of age over time.[7] With a standard deviation of age equal to 13.75 (in 2010), we also find that the mean and standard deviation of age are of roughly the same magnitude, which corresponds to the mean variance relationship for exponentially distributed variables. The oldest firms in the population are all 113 years old, and there are 110 such firms, which means that we cannot completely rule out right-censoring, although we consider right-censoring to be negligible given our primary focus on firms with ages of up to 40 years.

[4] See also Coad et al., 2014, p536.

[5] By adjusting for average industry sales, $\overline{sales}_{j,t}$, growth for a firm i active in industry j can be expressed by $growth_{i,t} = \log(sales_{i,t}/\overline{sales}_{j,t}) - \log(sales_{i,t-1}/\overline{sales}_{j,t-1})$, which in turn can be expressed $growth_{i,t} = \log\ (sales_{i,t}\ /sales_{i,t-1}) - \log(\overline{sales}_{j,t}/\overline{sales}_{j,t-1})$.

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

[7] The mode is not reported here, because the distribution is not monotone but multimodal.

Figure 2 shows the kernel density plots for annual sales growth rates for different age groups during 2010. 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.

[Figure 2 about here please]

Figure 3 contains further analysis of how the first four moments of the growth rate distribution (i.e. the mean, standard deviation, skewness and kurtosis) vary with age. The top-left panel shows that the mean growth rate is the highest in the first observed period (i.e. year 2),[8] 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 Figure 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 Figure 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 rates distribution becomes more heavy-tailed, and further from the Gaussian case as firms age.

[Figure 3 about here]

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 with age less than 5 years show higher average growth rates and higher standard deviation than older age categories.

[Table 1 about here]

[8] 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.

To get a first impression of the relationship between intertemporal growth rates, we look at the bivariate density of sales growth of consecutive 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 by the aid of a contour plot, illustrated through 20 shades of grey. The darker the color, the higher the frequency of firms with the intertemporal pair of sales growth rates. The bivariate frequency is scaled logarithmically, which means that the number of firms within a shade corresponds to the exponent of that log-frequency. The bivariate distribution found in the figure is unimodal with the black center, indicating that many firms have growth rates close to zero in both periods. Looking at the four different quadrants of sales growth contained in the plane when growth in either period ranges from [-2,2], every non-white shade indicates that some number of firms are present. For example, firms in the upper right quadrant (with growth in the range [0,2] in both periods) experienced high positive growth rates in both 2010 and 2009. The white spot in the top right corner suggests that no firms experienced $growth_{i,t}$ = 2 in consecutive periods.

[Figure 4 about here]

4. METHOD

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 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 the following data generating process, which is also used in previous research into growth rate autocorrelation (Coad, 2007; Coad and Hölzl, 2009; Bottazzi et al., 2011):

$$growth_{i,t} = \mu + \gamma size_{i,t-1} + \theta growth_{i,t-1} + \epsilon_{i,t}, \qquad (1)$$

In this model, growth is governed by three parameters. The first is the constant term, μ, that captures average growth rates; and the second parameter, γ, 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 firm size the previous period (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 $\gamma = 0$, which means that there are no effects on growth from lagged size. The other two scenarios that may occur in addition to LPE is $\gamma > 0$ and $\gamma < 0$, which in the first case means that growth becomes explosive as they grow increasingly faster when they become larger. Evidently this scenario can only be temporary and does not result in a steady state distribution for firm size. The other case ($\gamma < 0$) 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 θ, which refers to the effect from lagged growth rates, i.e. whether growth rates are persistent. This parameter is also intimately linked to the LPE. Should $|\theta| > 0$, such that growth rates are correlated, growth can be envisioned to either encourage or discourage growth, which eventually results in a dependence between firm size and growth (Chesher, 1979). Thus, in order for the LPE to be fulfilled, the condition $\theta = 0$ also needs to be fulfilled in addition to $\gamma = 0$. 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 last term is a disturbance term $\epsilon_{i,t}$. Our choice of estimator is based on the particularities of this term, which inherits the particular 'tent-shape' that characterize the distribution of firm-growth rates, as seen in Figure 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 dynamic 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; 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 tend 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 than OLS (Bottazzi et al., 2011).[9]

[9] In further robustness analysis, we repeated our regressions using OLS instead of LAD (and using both sales growth and employment growth as dependent variables). Our results were broadly similar in the sense that autocorrelation was more positive in the early years and quickly decreased, and remained relatively low in the remaining years. However, our OLS estimates were not precisely defined, and the autocorrelation coefficients for employment growth appeared to be overall more positive (for all ages) than the autocorrelation coefficients for sales growth.

Note also that the smallest possible age in which equation (1) can be estimated is when age is three. This is because lagged growth, i.e. growth at time $t-1$ is constructed from information on size at time $t-2$. Finally, equation (1) is estimated by robust standard errors.[10]

5. RESULTS

5.1 Main analysis

In this section we first present the results from estimating equation (3) for the complete age distribution of firms. We then partition the sample of firms into five different age categories from young to old.

Table 2 column (1) contains the median regression results for the full sample. The coefficient on lagged growth is negative (-0.031) and highly significant, indicating that firm growth is overall marked by negative growth rate autocorrelation. Since we estimate a double log model the coefficients can be interpreted as elasticities, measuring the effect of a 1% change of sales growth in period *t-1* on sales growth in period *t*. The results for the full sample (column (1)) thus indicate that a 1% change of sales growth in period *t-1* is associated with 0.031% decrease in sales growth in period *t*.

[Table 2 about here]

Gibrat's (1931) prediction that size is independent of growth rates can also be rejected. We observe a slightly positive relationship between growth rate and lagged size for the full sample (coefficient = 0.004), although the coefficient is negative when we focus on the subsample of firms aged 0-4 (see column (2); coefficient = -0.014).

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.

The results for the different age categories are presented in columns (2)-(6) of Table 2. Firms that are younger than 5 years show a positive and significant autocorrelation coefficient for the median firm, with a 1% increase in growth rates resulting in a 0.012% increase in growth rates in the following year. However, the estimated growth autocorrelation coefficient turns negative for older firms. This implies that positive growth rates tend to be followed by less positive growth rates, and that negative growth rates are followed by less negative growth rates. According to the results, a 1% increase in sales growth in year *t-1* will lead to a decrease in sales growth in year *t* of between 0.045% to 0.061% for firms that are five years or older. Hence, the autocorrelation coefficient is observed to be positive for the youngest age category (up to 4 years), but turns negative for all the older age categories.

[10] All median regression estimations are performed in Stata using the 'qreg, vce(robust)' command. Bootstrapping our standard errors was not a viable option due to the numerous regressions undertaken at each age. Clustered standard errors showed unstable behavior in the tails of the distributions, which inhibited convergence of the estimator.

We continue our investigation by plotting the evolution of sales growth for each age (i.e. 40 datapoints for ages 3-40) and growth quantile (Figure 5). In contrast to the results presented in Table 2, these results are based on estimations of equation (1). The result presented in Figure 5 shows that growth autocorrelation is positive for start-ups, but turns negative shortly afterwards, and remains negative or insignificant as firms grow older.

[Figure 5 about here]

5.2 Size disaggregation

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 consider it worth disaggregating our analysis by size.

A first concern was that one-person firms (also known as solo self-employed individuals), which are very numerous and make up a large share of the total number of firms, 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. All results remained qualitatively similar, however.[11]

In further analysis, we split our sample into firms with up to 9 employees, and firms with 10 or more employees, evaluated as the average number of employees over the periods $t-1$ and $t-2$. The results are plotted in Figures 6a and 6b. When we focus on the sales growth correlations for small firms (up to 9 employees), Figure 6a shows that the autocorrelation remains similar to that of the full sample, although standard errors seem to increase slightly. Figure 6b reports how autocorrelation varies with firm age, for firms with 10 or more employees. Firms with 10+ employees have a slightly positive autocorrelation in the first years, which then decreases the following years, and remains stable at negative values for the rest of the time. Based on these plots, it is clear that the initial growth spurt reflected in the aggregate is not exclusively a function of firm size.

[Figures 6a and 6b about here]

5.3 Surviving firms

One possible explanation for our finding of positive autocorrelation in the early years relates to selection effects – it might be possible that some short-lived firms experience two successive periods of decline (hence, positively-correlated growth across years) just 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

[11] These results are available upon request.

spurt their growth stabilizes as they reach a ‘steady-state’ scale of operation or ‘optimal size’.[12] Ideally, we would investigate selection 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 follow 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. More specifically, we measure the growth rate autocorrelation of firms of different ages, where the dependent variable is the annual growth rate measured into 2006, and inclusion in the sample is conditional on survival into 2010.

The results are shown in Figure 7. Similar to our previous results, we see that growth rate autocorrelation is positive in the first year, and decreases relatively slowly in the post-entry years, before again stabilizing at a level of negative growth rate autocorrelation for older firms. The biggest difference seems to be that, when focusing on survivors only, the initial growth spurt is qualitatively similar at the outset (for the youngest firms) to the results when only large firms were included (Figure 6b). At ages above 10 years, however, autocorrelation for surviving firms turns slightly more negative than that for the large firms. Overall, we can confirm that our main analysis is not driven by spurious selection effects, but instead that the observed patterns in growth rate autocorrelation over age relate to internal developmental factors in firms.

[Figure 7 about here]

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). 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.

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. However, sales growth autocorrelation turns increasingly negative for older firms. We thus found no support for notions that older firms should have a high degree of growth persistence due to learning effects or well-established capabilities. Instead our results support theories arguing that older firms might have problems in adapting their strategies to changing market conditions, whereas new firms seek to grow in order to achieve a minimum efficient scale and overcome their ‘liability of newness’ (Cabral, 1995).

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

However, once they have survived the first few years it seems that their growth loses its momentum.

Our analysis does not come without limitations. One question is whether our results can be generalized to other contexts. We believe that this is likely since Coad et al. (2013b) reported similar results for Spain, although their study was vulnerable to selection bias. Nevertheless, we would welcome further investigations in other contexts.

Further research could 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, 2009; Coad et al., 2013a).

ACKNOWLEDGEMENTS: We would like to thank Martin Carree, Marc Cowling, Michaela Niefert, and participants at ZEW (Mannheim) and the 2014 Babson College Entrepreneurship Research Conference (London, Ontario) for valuable comments and suggestions. The usual caveat applies.

REFERENCES

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.

Audretsch, D.B. (1995). Innovation, growth and survival. International Journal of Industrial Organization 13, 441-457.

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.

Barba Navaretti, G., Castellani, D., & Pieri, F. (2014). Age and firm growth: evidence from three European countries. Small Business Economics, 43(4), 823-837.

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.

Bottazzi G., Secchi A., (2006). Explaining the distribution of firm growth rates. Rand Journal of Economics 37 (2), 235-256.

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

Cabral L., (1995) Sunk Costs, Firm Size and Firm Growth. Journal of Industrial Economics 43(2), 161-172.

Capasso M, Cefis E, Frenken K (2014). On the existence of persistently outperforming firms. Industrial and Corporate Change 23 (4), 997–1036.

Caves, R. E. (1998). Industrial organization and new findings on the turnover and mobility of firms. *Journal of Economic Literature*, 36(4), 1947–1982.

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

Coad A., 2009. The Growth of Firms: a Survey of Theories and Empirical Evidence. Edward Elgar, Cheltenham, UK and Northampton, MA, USA.

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

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.

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.

Coad A, Frankish JS, Nightingale P, Roberts RG (2014). Business experience and start-up size: Buying more lottery tickets next time around? Small Business Economics 43 (3), 529-547.

Davidsson, P. and 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.

Daunfeldt, S-O., Elert, N., and 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.

Daunfeldt, S-O., and Halvarsson, D. (2015) "Are high-growth firms one hit wonders? Evidence from Sweden", *Small Business Economics,* 44, 2, 361-383.

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.

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

Denrell J., Fang C., Liu C., (2015). Chance Explanations in the Management Sciences. Organization Science, in press.

Dunne, T., M. Roberts and L. Samuelson (1989), 'The growth and failure of US manufacturing plants', Quarterly Journal of Economics, 104(4), 671–698.

Evans, D.S. (1987), 'The relationship between firm growth, size and age: estimates for 100 manufacturing industries', Journal of Industrial Economics, 35, 567–81.

Fizaine, F. (1968), 'Analyse statistique de la croissance des entreprises selon l'âge et la taille', Revue d'économie Politique, 78, 606–20.

Folta T.B., Delmar F., & Wennberg K. (2010). Hybrid entrepreneurship. *Management Science*, 56 (2), 253-269.

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.

Garnsey E. (1998). A Theory of the Early Growth of the Firm. Industrial and Corporate Change, 7 (3), 523-556.

Garnsey E., Heffernan P., (2005). Growth Setbacks in New Firms. Futures, 37 (7), 675-697.

Geroski, P.A., (2000). The Growth of Firms in Theory and in Practice. Pages 168-186 in Nicolai Foss and Volker Mahnke (eds): Competence, governance and entrepreneurship. Oxford University Press: Oxford, UK.

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

Gilbert BA, McDougall PP, Audretsch DB (2006). New venture growth: a review and extension. Journal of Management 32, 6, 926-950.

Greiner, L.E., (1998). Evolution and revolution as organizations grow. Harvard Business Review, May-June, 55-67.

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

Headd B., & Kirchhoff (2009). The growth, decline and survival of small businesses: an exploratory study of life cycles. *Journal of Small Business Management*, 47(4), 531-550.

Helfat, C E (2007). Stylized facts, empirical research and theory development in management. Strategic Organization 5(2), 185-192.

Huergo E., Jaumandreu J., (2004). How does probability of innovation change with firm age? Small Business Economics 22, 193-207.

Lawless, M., (2014). Age or size? Contributions to job creation. Small Business Economics 42:815–830.

Levinthal D.A., (1991). Random walks and organizational mortality. Administrative Science Quarterly 36 (3), 397-420.

Lotti, F., Santarelli, E., & Vivarelli, M. (2003). Does Gibrat's Law hold among young, small firms?. *Journal of Evolutionary Economics*, 13(3), 213-235.

Lotti F., Santarelli E., & Vivarelli M. (2009). Defending Gibrat's Law as a long-run regularity. *Small Business Economics*, 32, 31-44

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.

Parker (2004). *The Economics of Self-Employment and Entrepreneurship*. Cambridge University Press.

Parker SC, Storey DJ, & van Witteloostuijn A., (2010). What happens to gazelles? The importance of dynamic management strategy. *Small Business Economics* 35, 203-226.

Phillips BD, Kirchhoff BA (1989). Formation, growth and survival; small firm dynamics in the US economy. Small Business Economics 1, 65-74.

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.

Robson, P. and R. Bennett (2000), ‘SME growth: the relationship with business advice and external collaboration’, Small Business Economics, 15(3), 193–208.

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.

Sorensen J.B., & Stuart, T.E. (2000). Aging, Obsolescence, and Organizational Innovation. *Administrative Science Quarterly*, 45, 81-112

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(6568), 804-806.

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

Sutton, J. (1997). Gibrat’s legacy. *Journal of Economic Literature*, 35(1), 40–59.

Tornqvist L., Vartia P., Vartia Y.O. (1985). How Should Relative Changes Be Measured? American Statistician 39(1), 43-46.

Yasuda, T. (2005), ‘Firm growth, size, age and behavior in Japanese manufacturing’, Small Business Economics, 24(1), 1–15.

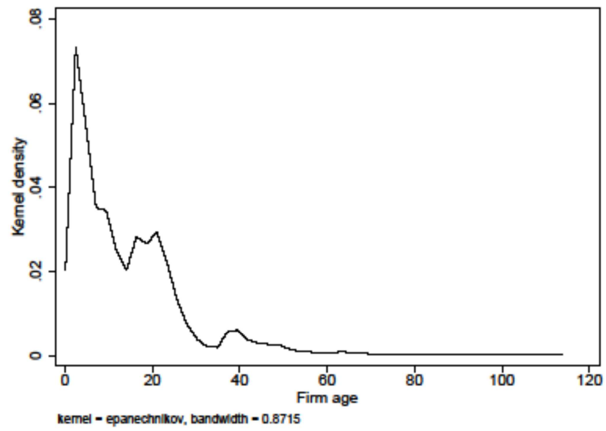

Figure 1. The age distribution of firms in 2010. Frequencies of firms observed for each year of the age distribution.

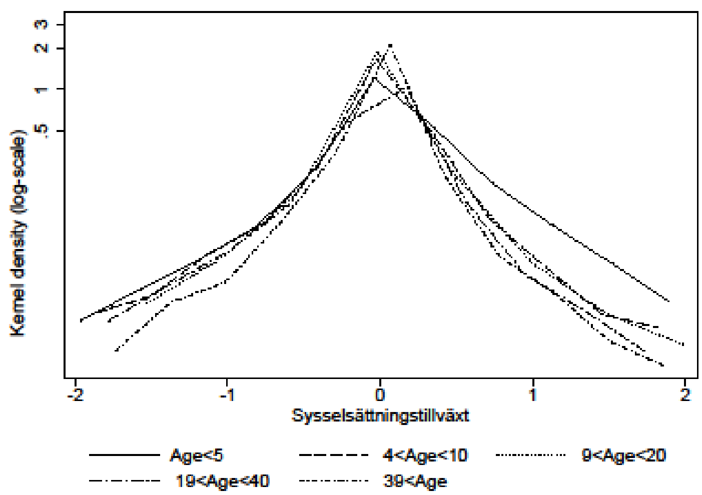

Figure 2. Kernel density plot of sales growth in 2010

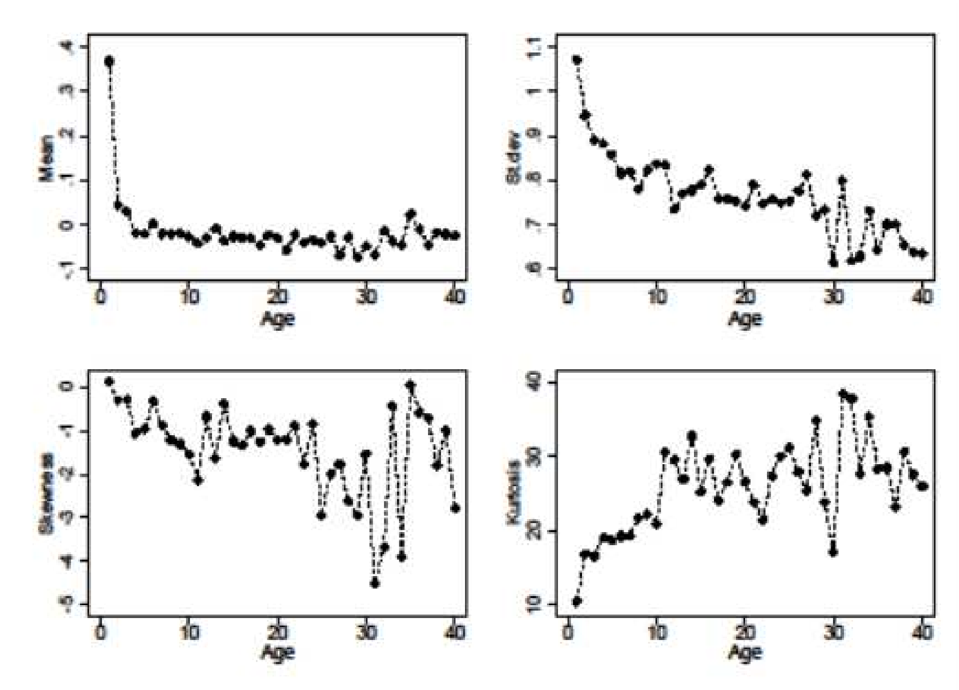

Figure 3. Mean, standard deviation, skewness, and kurtosis of growth rates over age

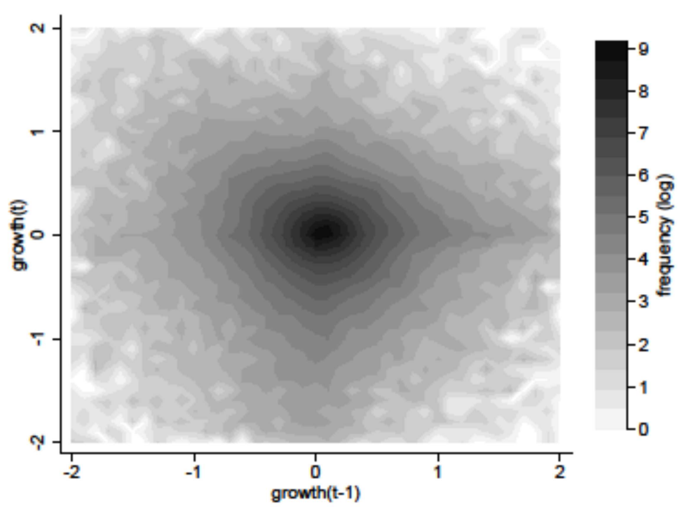

Figure 4. Contour plot for pairs of consecutive growth rates (i.e. growth(t-1) and growth(t)) in 2010 (all firms)

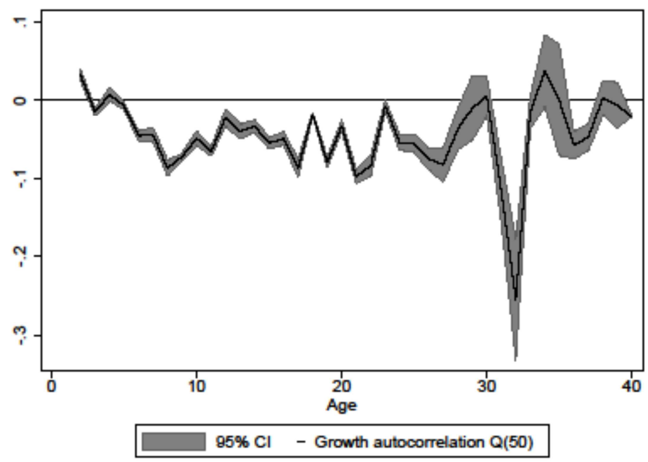

Figure 5. Median regression for ages 3- 40. Each datapoint corresponds to an estimate of θ from equation (1) for each year. Hence, this figure is based on 38 estimated coefficients (and standard errors) obtained from 38 regressions, one for each year.

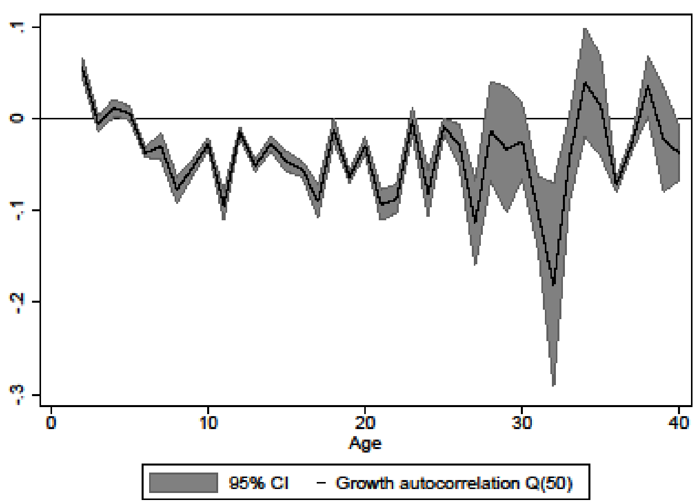

Figure 6a: Size disaggregation analysis: firms with up to 9 employees. Median regressions for ages 3-40. Each datapoint corresponds to an estimate of θ from equation (1) for each year. Hence, this figure is based on 38 estimated coefficients (and standard errors) obtained from 38 regressions, one for each year.

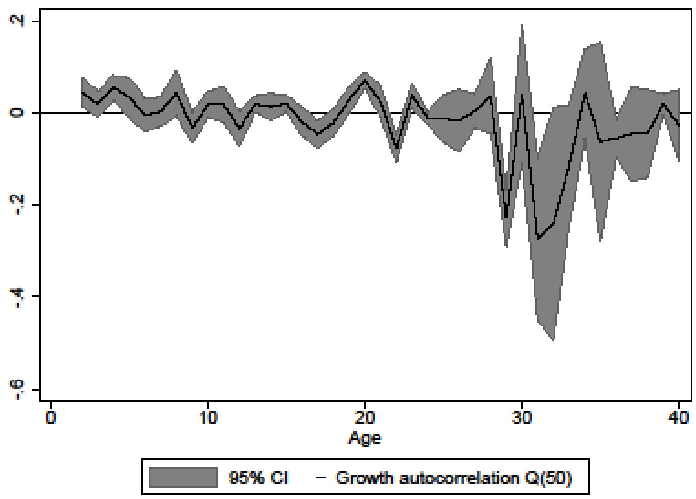

Figure 6b: Size disaggregation analysis: firms with 10 or more employees. Median regressions for ages 3-40. Each datapoint corresponds to an estimate of θ from equation (1) for each year. Hence, this figure is based on 38 estimated coefficients (and standard errors) obtained from 38 regressions, one for each year.

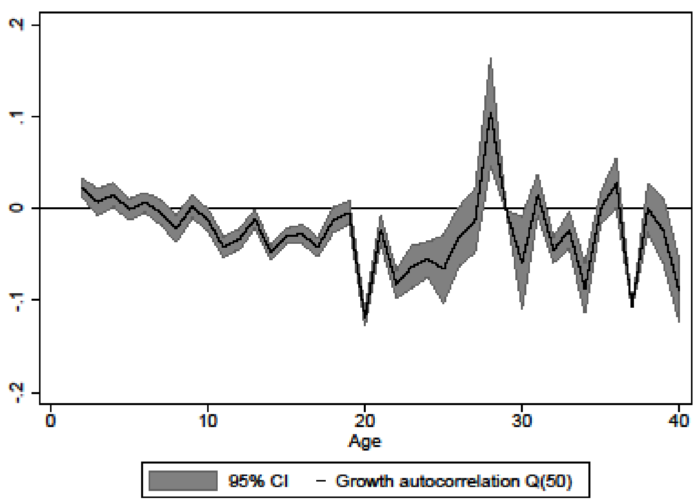

Figure 7: Median regressions for ages 3-40: Regressions in 2006 conditional on survival to 2010. Each datapoint corresponds to an estimate of θ from equation (1) for each year. Hence, this figure is based on 38 estimated coefficients (and standard errors) obtained from 38 regressions, one for each year.

Table 1. Description of sales growth by age categories

Age	**Obs.**	**Mean**	**St.dev**	**Min**	**Max**
0 – 4 years	39085	0.110	0.959	-8.793	9.574
5 – 9 years	39933	-0.016	0.834	-9.2573	8.795
10 – 19 years	55185	-0.030	0.792	-11.589	13.058
20 – 39 years	49139	-0.035	0.748	-9.958	9.132
40+ years	13301	-0.020	0.702	-10.356	7.249
All firms	196643	0.000	0.822	-11.589	13.058

Table 2. Regression estimation of equation (3) for all firms in 2010. Full sample, and subsamples disaggregated by age. Standard errors in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Sales Growth (2010)	All firms	0-4 years	5-9 years	10-19 years	20-39 years	40+ years
L.growth	-0.031***	0.012***	-0.045***	-0.050***	-0.054***	-0.061***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)
L.log(size)	0.004***	-0.014***	0.002***	0.004***	0.007***	0.007***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
L.log(age)	-0.007***	0.015**	-0.005	-0.016***	-0.002	-0.019***
	(0.001)	(0.007)	(0.006)	(0.005)	(0.004)	(0.005)
Constant	0.037***	0.012	0.038***	0.058***	0.020	0.088***
	(0.002)	(0.008)	(0.012)	(0.012)	(0.015)	(0.021)
Observations	177,496	29,045	37,223	57,551	42,301	11,376
Pseudo R2	0.00102	0.00132	0.00147	0.0019	0.00252	0.00416

Note: *** p<0.01, ** p<0.05, * p<0.10

APPENDIX 1: **<u>FOR REVIEWERS ONLY, NOT INTENDED FOR PUBLICATION.</u>** Quantile regression results, across the quantiles.

Some scholars may argue that it is of little interest to estimate the effect of firm age on the growth persistence of the average firm, when the average firm has marginal growth rates. Furthermore, there is increasing attention from scholars and policymakers on High-Growth Firms that are found at the upper end of the growth rate distribution. Methods that focus on the conditional mean of the growth rate distribution thus miss the more complex dynamics that might be present in other parts of the growth rate distribution.

Firm growth rates tend to follow the Laplace distribution (Stanley et al. 1996; Bottazzi and Secchi, 2006; Bottazzi et al. 2011), with most firms not growing while a few high-growth firms grow very fast. This makes OLS estimation less attractive, since it is of little interest to estimate the average effect of firm age on growth persistence when the median and the average firm have marginal growth rates. In line with previous work (Fotopoulos and Louri, 2004; Coad and Rao, 2008; Reichstein et al., 2010; Capasso et al., 2014) we now estimate quantile regression models to take explore how the relationship between firm age and growth persistence might differ across the growth rate distribution.

Table A1.1 shows the regression results for the full sample, while Tables A1.2 to A1.6 report the results for subsamples disaggregated by age. The rate of growth autocorrelation becomes increasingly negative for the upper quantiles when all firms are included in the model (Table 2). The trend goes from 0 at the lowest (q=0.1) quantile to -0.105 for the 10 percent fastest growing firms at the 90% quantile. Since we estimate a double log model, the coefficients can be interpreted as elasticities, measuring the effect of a 1% change of sales growth in period t-1 on sales growth in period t. The results for the median firm (q=0.5) thus indicate that a 1% change of sales growth in period t-1 is associated with 0.031% decrease in sales growth in period t, whereas a corresponding increase is associated with a 0.105% decrease in sales growth in period t for the 90% quantile. Hence, given the increasingly negative effects found for higher quantiles, the faster a firm grows in year *t-1*, the more negative is the correlation with growth rates in year *t*.

Gibrat's (1931) prediction that size is independent of growth rates can also be rejected. We observe increasing growth rates from a larger size for firms in the median quantile, and below. Since most of these firms by definition experience negative growth rates in time t, having a large size in *t-1* is associated with having a less negative growth rate in *t*.

Firm age is negatively related to growth persistence for the median firm (q=0.50), indicating that sales growth is decreasing more for older firms following a growth period. According to the results presented in Table A1.1, an additional one year of age results in -0.05% lower growth rates (size_(i,t)/size_(i,t-1)) on average, evaluated for a firm with the average age of 14 years (-0.007*1/14*100=-0.05). This effect of firm age on growth persistence is even more negative for higher growth quantiles, with an additional year translating into -0.36% lower growth rates for the fastest growing firms (q=0.90).

The results for the different age categories are presented in Tables A1.2-A1.6. Regarding the quantile regression solutions at the median, our comments can be found in the text. Our results indicate that the estimated growth autocorrelation coefficients are negative and significant for the fastest growing firms among all age categories (at the 90% quantile), suggesting that high growth rates in year *t-1* are followed by lower growth rates in year *t*. These results confirm previous findings that high-growth rates are unlikely to be repeated (Parker et al., 2010; Hölzl, 2014; Daunfeldt and Halvarsson, 2015). The size of the effect is, however, much smaller for young firms compared to older firms. For example, a 1% sales growth increase in year *t-1* for firms that are younger than 5 years will lead to a decrease in growth rates for these firms with -0.035% in year *t* (see column (5) of Table A1.2); while a corresponding increase for fast-growing firms that are aged 40 or more will result in a -0.155% growth rate decrease (see column (5) of Table A1.6).

Table A1.1. Regression estimation of equation (3) for all firms in 2010. Full sample.

All firms	(1)	(2)	(3)	(4)	(5)
Sales Growth (2010)	$q = 0.1$	$q = 0.25$	$q = 0.50$	$q = 0.75$	$q = 0.90$
$L.growth$	0.004	-0.020***	-0.031***	-0.071***	-0.105***
	(0.006)	(0.002)	(0.001)	(0.001)	(0.003)
$L.\log(size)$	0.087***	0.031***	0.004***	-0.027***	-0.083***
	(0.002)	(0.000)	(0.000)	(0.000)	(0.001)
$L.\log(age)$	0.048***	0.012***	-0.007***	-0.033***	-0.051***
	(0.004)	(0.001)	(0.001)	(0.001)	(0.003)
Constant	-0.714***	-0.201***	0.037***	0.294***	0.660***
	(0.012)	(0.004)	(0.002)	(0.003)	(0.007)
Observations	177,496	177,496	177,496	177,496	177,496
Pseudo R2	0.0239	0.00748	0.00102	0.0167	0.0705

Standard errors in parentheses*** p<0.01, ** p<0.05, * p<0.10

Table A1.2. Regression estimation of equation (3) for firms with < 5 years of age in 2010

Age < 5	(1)	(2)	(3)	(4)	(5)
Sales Growth (2010)	$q = 0.1$	$q = 0.25$	$q = 0.50$	$q = 0.75$	$q = 0.90$
$L.growth$	0.032**	0.016***	0.012***	-0.002	-0.035***
	(0.013)	(0.003)	(0.002)	(0.004)	(0.005)
$L.\log(size)$	0.098***	0.020***	-0.014***	-0.068***	-0.151***
	(0.006)	(0.001)	(0.001)	(0.002)	(0.003)
$L.\log(age)$	0.016	0.045***	0.015**	-0.031***	-0.079***
	(0.041)	(0.011)	(0.007)	(0.010)	(0.021)
Constant	-0.694***	-0.236***	0.012	0.313***	0.763***
	(0.045)	(0.012)	(0.008)	(0.012)	(0.024)
Observations	29,045	29,045	29,045	29,045	29,045
Pseudo R2	0.0159	0.00240	0.00132	0.0210	0.0813

Standard errors in parentheses*** p<0.01, ** p<0.05, * p<0.10

Table A1.3. Regression estimation of equation (3) for firms with 4 < Age <10 years in 2010

4 < Age <10	(1)	(2)	(3)	(4)	(5)
Sales Growth (2010)	$q = 0.1$	$q = 0.25$	$q = 0.50$	$q = 0.75$	$q = 0.90$
$L.growth$	0.003	-0.036***	-0.045***	-0.088***	-0.128***
	(0.009)	(0.005)	(0.001)	(0.002)	(0.009)
$L.\log(size)$	0.105***	0.034***	0.002***	-0.039***	-0.112***
	(0.004)	(0.002)	(0.001)	(0.001)	(0.002)
$L.\log(age)$	0.044	0.002	-0.005	-0.025***	-0.056**
	(0.041)	(0.015)	(0.006)	(0.010)	(0.023)
Constant	-0.734***	-0.180***	0.038***	0.289***	0.702***
	(0.078)	(0.028)	(0.012)	(0.018)	(0.045)
Observations	37,223	37,223	37,223	37,223	37,223
Pseudo R2	0.0185	0.00571	0.00147	0.0183	0.0827

Standard errors in parentheses*** p<0.01, ** p<0.05, * p<0.10

Table A1.4. Regression estimation of equation (3) for firms with 9 < Age <20 years in 2010

9 < Age < 20 Sales Growth (2010)	(1) $q = 0.1$	(2) $q = 0.25$	(3) $q = 0.50$	(4) $q = 0.75$	(5) $q = 0.90$
$L.growth$	-0.006	-0.038***	-0.050***	-0.094***	-0.121***
	(0.011)	(0.003)	(0.001)	(0.001)	(0.007)
$L.\log(size)$	0.090***	0.034***	0.004***	-0.028***	-0.085***
	(0.002)	(0.001)	(0.000)	(0.001)	(0.001)
$L.\log(age)$	0.170***	0.031***	-0.016***	-0.071***	-0.131***
	(0.029)	(0.010)	(0.005)	(0.007)	(0.017)
Constant	-1.034***	-0.255***	0.058***	0.387***	0.850***
	(0.079)	(0.026)	(0.012)	(0.019)	(0.045)
Observations	57,551	57,551	57,551	57,551	57,551
Pseudo R2	0.0236	0.00824	0.00190	0.0174	0.0730

Standard errors in parentheses*** p<0.01, ** p<0.05, * p<0.10

Table A1.5. Regression estimation of equation (3) for firms with 19<Age<40 years in 2010

19 < Age Sales Growth (2010)	(1) $q = 0.1$	(2) $q = 0.25$	(3) $q = 0.50$	(4) $q = 0.75$	(5) $q = 0.90$
$L.growth$	-0.026**	-0.032***	-0.054***	-0.096***	-0.121***
	(0.012)	(0.004)	(0.001)	(0.003)	(0.008)
$L.\log(size)$	0.090***	0.035***	0.007***	-0.020***	-0.068***
	(0.002)	(0.001)	(0.000)	(0.001)	(0.002)
$L.\log(age)$	0.110***	0.040***	-0.002	-0.016**	-0.020
	(0.027)	(0.010)	(0.004)	(0.007)	(0.021)
Constant	-0.910***	-0.298***	0.020	0.231***	0.522***
	(0.088)	(0.032)	(0.015)	(0.023)	(0.066)
Observations	42,301	42,301	42,301	42,301	42,301
Pseudo R2	0.0304	0.0115	0.00252	0.0144	0.0604

Standard errors in parentheses*** p<0.01, ** p<0.05, * p<0.10

Table A1.6. Regression estimation of equation (3) for firms with Age>39 years in 2010

19 < Age Sales Growth (2010)	(1) $q = 0.1$	(2) $q = 0.25$	(3) $q = 0.50$	(4) $q = 0.75$	(5) $q = 0.90$
$L.growth$	0.005	-0.030***	-0.061***	-0.132***	-0.155***
	(0.024)	(0.005)	(0.003)	(0.006)	(0.014)
$L.\log(size)$	0.064***	0.022***	0.007***	-0.009***	-0.049***
	(0.004)	(0.001)	(0.001)	(0.001)	(0.003)
$L.\log(age)$	-0.106**	-0.016	-0.019***	-0.009	0.089***
	(0.047)	(0.011)	(0.005)	(0.008)	(0.029)
Constant	-0.062	-0.069*	0.088***	0.195***	0.077
	(0.182)	(0.042)	(0.021)	(0.033)	(0.111)
Observations	11,376	11,376	11,376	11,376	11,376
Pseudo R2	0.0318	0.0115	0.00416	0.0163	0.0636

Standard errors in parentheses*** p<0.01, ** p<0.05, * p<0.10

APPENDIX 2: **FOR REVIEWERS ONLY, NOT INTENDED FOR PUBLICATION.**
Contour plots for pairs of consecutive growth rates in 2010, for five age groups.

The Figure below provides information on contour plots for different age groups, which has the potential to give impressions on patterns of growth rate autocorrelation over age. However, we would prefer not to attempt to publish these diagrams because of technical difficulties. The problem is that the shading scales on the left of each of the four plots are different for each plot, making it difficult to compare the plots. However, it is not trivial to restrict the plots to having the same scale. When we redid these four plots with the restriction that they have the same scale, we obtained some very (very) ugly looking plots. This is presumably because of large differences between the number of observations in each age group. It appears that we can't have visually appealing graphs, as well as common scales across graphs. Whether we compute the relative frequency or whether we use log of the firm count as z-variable, we were unsuccessful in producing satisfactory plots. Another concern about the comparability of these plots is that each shading scale is simply read as the logarithm of the number of firms that has a particular position in autocorrelation space. Unfortunately, using the logarithm may distort some of the pattern, which is why the plots maybe shouldn't be overemphasized, as they are potentially quite sensitive to the choices made as regards the size of the grid, and the frequency variable used, especially in disaggregated age groups (but this is less of a problem for the aggregate contour plot in Figure 4). To summarize, then, we found no easy solution regarding how to present contour plots for age groups in a way that the plots could be compared to each other, and therefore prefer not to present them at all in the final manuscript.

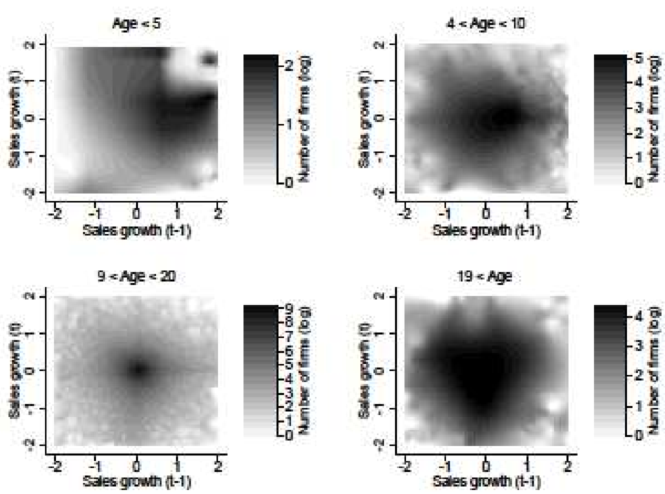

Figure A2.1 Contour plot for pairs of consecutive growth rates (i.e. growth(t-1) and growth(t)) in 2010 (all firms) divided by different age classes

APPENDIX 3: **<u>FOR REVIEWERS ONLY, NOT INTENDED FOR PUBLICATION.</u>** Ordinary Least Squares (OLS) estimations.

Our baseline estimator was the median regression estimator,[13] which is the estimator of choice when the dependent variable is not Gaussian but Laplace-distributed (Bottazzi et al., 2011). OLS and median regressions can provide rather different estimates of the autocorrelation coefficient (see e.g. Bottazzi et al., 2011, Table 3), and so we prefer median regressions over OLS for theoretical reasons (i.e. Laplace-distributed errors). In this appendix, however, we explore the robustness of our findings when we take an alternative and more widely-known estimator, i.e. Ordinary Least Squares (OLS). Figure A3.1 plots the OLS estimates of the coefficient on sales growth persistence for ages up to 40, with one regression for each year. In the first observed year (which corresponds to age three), the autocorrelation coefficient is slightly positive, but generally decreases in the following years until it stabilizes at a negative value. In later years, perhaps because of a smaller number of observations, the autocorrelation coefficient fluctuates more than in earlier years. Overall, however, our OLS estimates mirror our median regression estimates, in that the autocorrelation coefficient is positive at the beginning, but then decreases until ages of around 8-10, after which it stabilizes at a negative value of autocorrelation.

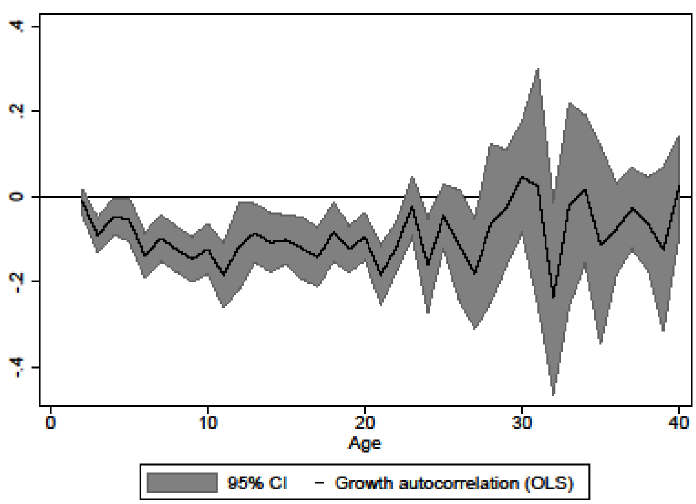

Figure A3.1: OLS estimation of autocorrelation of sales growth, for ages 3-40. Each datapoint corresponds to an estimate of θ from equation (1) for each year. Hence, this figure is based on 38 estimated coefficients (and standard errors) obtained from 38 regressions, one for each year.

[13] Also known as the Least Absolute Deviation estimator, or the L1 estimator, and effectively corresponds to quantile regression performed at the 50% quantile.

In our main analysis, we apply median regressions to analyze the growth of sales rather than employment, because the employment growth distribution has a mass point at zero, corresponding to the many firms that stay with exactly the same number of employees from one year to the next. These integer restrictions affecting employment growth (which are not problematic when growth is measured in terms of sales) can be problematic for median regressions, because the median growth rate autocorrelation often corresponds to relatively uninteresting cases of firms that don't change their number of employees from one year to the next, and the autocorrelation is often calculated as exactly zero. However, least squares regression is less affected by integer restrictions and the mass point at zero employment growth, and therefore provides a meaningful way of investigating autocorrelation in the growth of employment. We can therefore investigate whether our findings for sales growth also hold for employment growth.

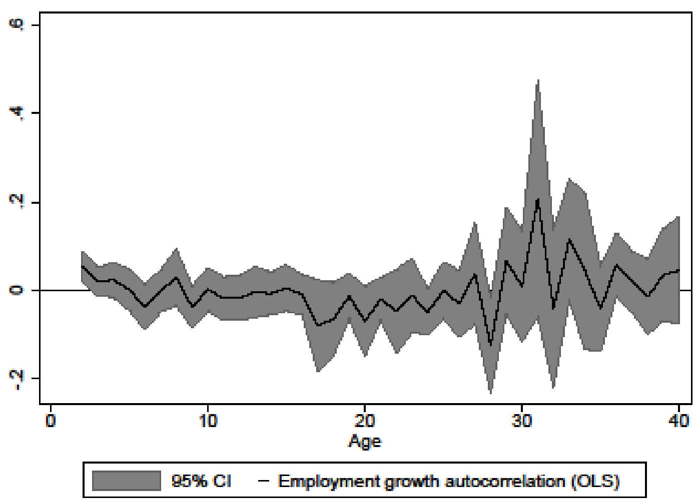

Figure A3.2: OLS estimation of autocorrelation of employment growth, for ages 3-40. Each datapoint corresponds to an estimate of θ from equation (1) for each year. Hence, this figure is based on 38 estimated coefficients (and standard errors) obtained from 38 regressions, one for each year.

Figure A3.2 shows how the autocorrelation coefficient for employment growth changes in the years after entry, until age 40. Some similarities with the results for sales growth can be mentioned – the autocorrelation starts off relatively high, with positive autocorrelation in the first few years, before decreasing and then remaining stable at these smaller values. Some differences can also be observed, however. The autocorrelation coefficient for employment growth seems to be overall less negative than what we observed for sales growth (compare Figure A3.2 with Figure A3.1 above). The autocorrelation coefficient also appears to increase in later years, although the estimates are not precisely defined – this finding would merit further investigation.