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FIRM AGE AND GROWTH PERSISTENCE

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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 autocorrelation, whereas it turns increasingly negative for older firms. It thus seems that the growth paths of older firms are buffeted around by environmental turbulence, and that older firms have challenges in adapting their strategies to changing market conditions, whereas new firms need to grow in order to achieve a minimum efficient scale.

INTRODUCTION

A key indicator of performance of new ventures is their post-entry growth (Parker, 2004), although the characteristics of new firm growth remain poorly understood (McKelvie and Wiklund, 2010). Building on previous entrepreneurship research into the growth paths of new ventures (Delmar et al., 2003; Coad et al., 2013a), we investigate how growth paths are moderated by firm age. A number of studies have indicated that firm age is an important determinant of firm growth, with younger firms growing faster than older firms (Haltiwanger et al., 2013).

However, we still lack knowledge on how firm age is influencing firm growth rates over time, and theories of how firm ageing processes influence growth paths give us no clear guidance. On the one hand, we may expect that young firms face a liability of newness (Stinchcombe, 1965). Translated to growth persistence, older firms may have more experience and foresight when it comes to their business environment, 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) also suggest that older firms may benefit from their greater business experience, and therefore have a higher degree of growth persistence than younger firms.

On the other hand, older firms might 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 have problems adapting their strategies to changing business conditions as well as increasing inertia and organizational rigidities. Young firms might also seek to achieve 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, growth will lose its momentum.

There is little empirical work on how growth autocorrelation varies over firm age. This 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." 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 overcome these problems by using a data-set with information 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 entrepreneurship research has had difficulties in obtaining data on the early years of new ventures (Bamford et al., 2004 Table 1), we are thus in a unique position to look at growth paths of firms of all ages.

Firm growth rates tend to follow the Laplace distribution (Stanley et al. 1996; Bottazzi and Secchi, 2003; Bottazzi et al. 2011), with most firms not growing while a few high-growth firms grow very fast. This makes OLS estimation unattractive 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. Following Fotopoulos and Louri (2004), Coad and Rao (2008), and Reichstein et al. (2010), we instead estimate quantile regression models to take into account that the relationship between firm age and growth persistence might differ across the growth rate distribution.

Our results indicate that young firms are characterized by positive growth autocorrelation, whereas the autocorrelation coefficient turns increasingly negative for older firms. Nascent ventures, therefore, enjoy positive persistence – a sort of 'success-breeds-success' dynamic – which lasts for fewer than ten years, until persistence becomes negligible for older firms. This finding can be related to the struggle for new ventures to grow and overcome the vulnerabilities related to their initial small scale. We can thus reject the hypothesis that older firms should have a high degree of growth persistence due to learning effects. Instead our results support theories arguing that older firms might have problems in adapting their strategies to changing market conditions, whereas new firms need to grow in order to achieve a minimum efficient scale.

THEORETICAL BACKGROUND AND PREVIOUS STUDIES

Early theoretical work on firm dynamics focused almost exclusively on how firm size was related to firm growth, whereas firm age received little attention. One the most studied hypothesis in the literature is whether Gibrat's (1931) law of proportionate effects holds, i.e., whether firm growth is independent of firm size (for overviews, see e.g., Sutton 1997; Caves 1998; Lotti et al. 2003). But more recently researchers have also started to include firm age as an explanatory variable in firm growth analysis. The results tend to indicate that younger firms in general grow faster than older firms (Coad, 2009). Daunfeldt et al. (2014) also indicated 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. Haltiwanger et al. (2013) even indicated that the relationship between firm size and firm growth disappears when controlling for firm age, suggesting that causality runs from age to growth and not from size to growth.

However, we still lack knowledge on how firm age influences the growth process of firms. Young firms might, for example, have higher growth rates but also more erratic growth paths than older firms. Existing theories of how firm ageing processes influence growth paths give us no clear guidance. One the one hand, we may expect that young firms face a liability of newness (Stinchcombe, 1965). Translated to growth persistence, older firms may have more experience and foresight when it comes to their business environment, which lead to longer planning horizons, 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) also suggest that older firms may benefit from their greater business experience, and therefore have a higher degree of growth persistence than younger firms.

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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. (2013) 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), Daunfeldt and Halvarsson (2012) and Hölzl (2014), who have found that high-growth firms are essentially one-hit wonders.

However, very few studies have previously investigated whether growth autocorrelation is related to firm age. One exception is Coad et al. (2013b), who analyzed whether autocorrelation coefficients changed when firms grow older using a panel of Spanish manufacturing firms during 1998-2006. Their results indicated that sales growth autocorrelation was positive for firms that were less than 5 years old, but then turned and stayed negative for older firms. However, these authors caution 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.

DATA

The main challenges when investigating the effects of firm age are data availability, and the necessity of a comprehensive representation of young firms. 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 previous been shown to be an unusually rich information source for entrepreneurship research (e.g. Davidsson et al., 2009; Wennberg et al., 2010; 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 (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, which we define as firms that have at least one employee and positive sales.

To measure firm growth we use the log-difference of firm size, i.e.

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

where firm size is measured using sales. 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 closely correlated. The correlation for all years between sales and employment in our data is 0.84, which is higher than in previous studies that have found that sales and employment growth are only modest correlated (Shepherd and Wiklund, 2009), presumably because of our rich coverage of small young firms. We have also performed all analyses with employment as growth indicator, and the results are very similar and available upon request. 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. 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 expected since we know that young firms have high exit rates (Lotti et al., 2003). Except for the hump around age 20 and 40 the distribution seems to display exponential decay (disregarding the discreteness of age). Compared to other studies on firm age we do not need to work with truncated or censored age distributions due to our complete coverage.

We find that the mean and standard deviation of age are both 14, which also corresponds to the mean variance relationship for exponentially distributed variables. The oldest firms in the population are 113 years old and amount to 110 firms, which mean that we cannot completely rule out right-censoring. But given its small extent we choose to dismiss right-censoring issues in the subsequent analysis.

Figure 2 shows the kernel density plots for annual sales growth for different age groups rates during 2010. Plotted on a semi-log axis the growth-rate distribution exhibits the typical tent shape. We also choose to apply a censoring for $|growth_{i,t}| > 2$ with the probability mass collected in ± 2. A striking feature of the figure is the upward-curling tails that would indicate, a slightly heavier distribution than the Laplace, which has longer tails than the Gaussian distribution. Moreover, the distribution of the youngest firms (age < 5 years) is different from that of older firms with more probability mass located at larger than zero growth rates. This indicates that younger firms are more likely than older firms to experience fast sales growth rates, confirming results by Coad et al. (2013b). However, in contrast to the findings presented by Coad et al. (2013b), the numbers of young firms in the middle of the growth rate distribution (i.e., with close to zero growth rates) are also a lot 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.

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.

To get a first idea over the relationship between intertemporal growth rates, we look at the bivariate density of sales growth of consecutive annual growth rates. Figure 3 is a representation of the bivariate density of sales growth in period t and $t-1$, and is in itself an important contribution to empirical work on growth autocorrelation. The frequency is projected into the plane by the aid of a contour plot, illustrated through 20 shades of grey. The darker the color is, the higher is 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 represents the many firms that do not grow, nor did grow in the previous period. Looking at the four different quadrants of sales growth contained in the plane $(-2,2) \times (-2,2)$, every non-white shade indicates that some number of firms are present. For example, firms in the upper right quadrant $(0,2) \times (0,2)$ experienced positive growth rates in both 2010 and 2009. The white spot in the top right corner suggests that no firms did experience consecutive growth rates at that rate.

In a similar way we have also constructed contour plots for the different age categories used above (Figure 4). While plot over all firms looks rather symmetric, the bivariate distribution of consecutive growth rates for different age categories are more heterogeneous. Looking at the contour plot for the youngest firms, we see a slight tendency that firms with negative growth rates in 2009 experienced positive growth rates in 2010. The same tendency can as easily be distinguished for the older firms. Perhaps most strikingly is the bottom right contourplot in Figure 4 that contains the oldest firms. These firms experience considerably less fluctuation in their growth rates over time, while their growth rates had roughly the same standard deviation in 2010 (Table 1) as for the age group 20-40 years.

METHOD

This paper follows in the tradition of modeling firm growth as a stochastic process. At any point in time, even if there are a multitude of different factors (internal and external) affecting the process of growth for the individual firm, the stochastic framework regards those factors as approximately random at the aggregate level. While some factors work to decrease growth, others cause it to increase. In the cross-sectional analysis of firm growth the combined effect of these forces amount to a probability distribution that describes the dynamic of firm growth (Singh and Whittington, 1975). Considering the probability distribution of growth rates, autocorrelation refers to a type of intra-distributional movement, where the position of past growth affects the position of future growth rates.

To model the dynamics of firm growth, we consider the following data generating process:

$$growth_{i,t} = (1-\beta)\alpha_i + (\beta-1)size_{i,t-1} + \sum_{s=1}^{k}\theta_s growth_{i,t-s} + \epsilon_{i,t}, \qquad (1)$$

where the parameter α_i captures time-invariant heterogeneous firm effects and δ_t time effects. The disturbance term $\epsilon_{i,t}$ is assumed to be independent and identically distributed. To analyze persistence we are interested in θ, which refers to the effect on current growth from lagged growth rates. The interpretation of θ is as follows; the percentage change of firm growth in t from a percent change in growth $t-1$. For example, if θ=0.2, then a 10 percent increase in growth in time $t-1$ would translate into an increase of 2 percent in growth in time t. Should $\theta = -0.2$, the effect on growth would instead be a decrease of 2 percent in time t. The model in (1) is closely related to Gibrat's Law of Proportionate Effect (LPE), which states that growth rates in time t are independent of size in the previous period $t-1$. This happens when $\beta = 1$, where β refers to the effect on growth from lagged size, and $\alpha_i = 0$. If $\beta > 1$, growth becomes explosive, where firms grow faster as they become larger. Evidently this scenario can only be temporary and does not result in a steady state distribution for firm size. If $\beta < 1$, size regresses to the mean, with smaller firms growing faster than large firms. In the Gibrat literature, growth autocorrelation is usually considered only in so far as it violates the LPE. If persistence is present in the form of state dependence, growth can be said to either encourage or discourage growth, eventually resulting in a dependence between firm size and growth (Chesher, 1979).

Equation (1) is used in Coad and Hölzl (2009) and Coad (2007) to study growth autocorrelation. Here we go one step further and derive (1) from the properties of $size_{i,t}$. Essentially (1) coincides with the Augmented Dickey Fuller test, which is known to follow from imposing an AR(2) structure on $size_{i,t}$, hence

$$size_{i,t} = \phi_0 + \phi_1 size_{i,t-1} + \phi_2 size_{i,t-2} + \epsilon_{i,t}. \qquad (2)$$

After subtracting $size_{\mathrm{i,t-1}}$ from both sides, and thereafter adding zero $\phi_2(size_{i,t-1} - size_{i,t-1})$ to the right hand side of (2), the expression becomes

$$growth_{i,t} = \phi_0 + (\phi_1 + \phi_2 - 1)size_{i,t-1} - \phi_2 growth_{i,t-1} + \epsilon_{i,t}, \qquad (3)$$

which is equivalent to (1) for $k = 1$. By deriving the model from an AR(2) process of $size_{i,t}$, the parameters β and θ in (1) can be related to ϕ_1 and ϕ_2 in (3) through, $\beta = \phi_1 + \phi_2$, and $\theta = -\phi_2$. Thus, it follows from this simple exercise, given the structure of size in (2), that growth persistence θ in the augmented Dickey-Fuller test, for $k = 1$, are implied from the sign of the second lag of firm size.

In order to estimate equation (3), we apply a quantile regression estimator. We do this for three reasons. First, there is a vast literature that analyses the fastest growing firms in the economy. Evidence suggests that these firms display a number of unique characteristics compared to other more slowly growing firms. There are therefore good reasons to expect that the persistence also differs regarding the fastest growing firms. A number of studies (Coad and Hölzl, 2009; Daunfeldt and Halvarsson, 2014) have also found that these firms display stronger negative persistence than other firms, which would imply that they often experienced strong negative growth rates in previous periods. Second, we know from previous studies that most firms do not grow from one year to another, which is also visible in Figures 2-4. This means that methods based on OLS estimation are inappropriate since it is of little interest to estimate the average effect of firm age on growth persistence when the average firm has marginal growth rates. 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. Third, given the characteristic non-Gaussian 'tent-shape' of the growth rates distribution, methods based on least squares are heavily dependent upon the normality assumption of the residuals. For leptokurtic distributions, least squares methods perform less well. Median regression or quantile regression, on the other hand, are especially well-suited to model disturbances that are Laplace-distributed, which is closely related to the observed growth-rate distribution. Compared to most previous studies that have applied quantile regression techniques, we use clustered standard errors (which are now available in standard computer packages) in all estimations to ensure against excess within-autocorrelation and heteroskedasticity in the error term.

RESULTS

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 four different age categories from young to old. To increase the number of observations in the category containing the oldest firms, for our regressions we merge firms with age 19 – 40 year with firms that have existed more than 40 years.

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 -0.111 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 percent change of sales growth in period *t-1* on sales growth in period *t*. The result for the 90% quantile thus indicates that a 1% change of sales growth in period *t-1* is associated with 0.111% decrease in sales growth in period *t*. Hence, given the increasingly negative effects found for higher quantiles, the faster a firm grows in t the more negatively does it correlate with growth rates in $t-1$.

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. Thus, even if Gibrat's law is rejected from $(\phi_1 + \phi_2 - 1) > 0$, the positive effect from $L.\log(size)$ is compatible with size mean reversion. As regards firm age it seems to exert a cushioning effect for the firms with lowest negative growth rates (q=0.1). The effect is symmetrical for higher quantiles, where a higher age translates into a slower growth rate. For the fastest growing firms, an additional 1 year of age results in -0.3% lower growth rates ($size_{i,t}/size_{i,t-1}$) on average, evaluated for a firm with the average age of 14 years ($-0.042 * 1/14 * 100 = -0.3$).

Next we present the results for the different age categories (Tables 3-6). The results indicate that the autocorrelation coefficient for young firms is closer to zero than it is for older firms. Firms that are younger than 5 years show no significant autocorrelation coefficients for most of the growth quantiles, while the fastest growing young firms have a negative and significant autocorrelation coefficient. The size of the effect is, however, much smaller for young firms compared to older firms. According to the results, a 1% increase in sales growth in period *t-1* will lead to a -0.04% decrease in sales growth in period *t* for the young fast growing firms. The corresponding figures for older firms are also negative, but the size of the estimated coefficients is more than twice as high. For example, a 1% sales growth increase in period *t-1* for firms that are older than 19 years will lead to a decrease in growth rates for these firms with -0.133%.

Finally, we continue our investigation by plotting the evolution of sales growth for each age (i.e. 40 datapoints for ages 1-40) and growth quantile (Figure 5). In contrast to the results presented in Tables 2-6, these results are based on estimations of equation (3) where standard errors are not clustered. The results presented in Figure 5 show that growth autocorrelation is positive for start-ups for all growth quantiles, but turns negative only after a few years. The trend is also more negative for firms with higher growth rates and stays negative for quantile 0.75 and 0.90, whereas it is not significantly different from zero in the other quantiles when the firm gets older.

SUMMARY AND CONCLUSIONS

Firm age has been argued to be one of the most important determinants of firm growth. However, we still know very little about how firm age influences growth over time. 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 age (that is, 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. However, sales growth autocorrelation turns increasingly negative for older firms. We thus found no support for the hypothesis that older firms should have a high degree of growth persistence due to learning effects. Instead our results support theories arguing that older firms might have problems in adapting their strategies to changing market conditions, whereas new firms need to grow in order to achieve a minimum efficient scale.

Our analysis therefore shows that the volatility of growth does not decrease with age, but rather that it increases. Firms do not learn how to smooth their growth over time – in fact, they appear to do worse in smoothing their growth, even since a relatively early age. This need not necessarily be interpreted, however, as evidence that firms become less able to evaluate the evolution of their environment. As time goes by, the environment in which firms operate seems to become more volatile. Firms are not in complete control of their environments. Our speculative interpretation is that firms learn how to deal with uncertainty as they age. They learn how to survive and thrive even in increasingly turbulent environments, which might throw younger firms off balance. The analogy would be similar to the behaviour of a surfer who stays afloat on a surfboard even as the sea gets choppier. The skilled surfer can stay afloat even on increasingly turbulent waves; and the aging firm is able to conduct its business even in increasingly volatile situations.

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REFERENCES

Arrow, K.J. (1962). The economic implications of learning by doing. *Review of Economic Studies*, 29, 155–173.

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.

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. (2003). Why are distributions of firm growth rates tent-shaped?. *Economic Letters*, 80(3), 415-420.

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

Capasso M, Cefis E, Frenken K (2013). On the existence of persistently outperforming firms. *Industrial and Corporate Change*, in press.

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., & 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.

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., & Johansson, D. (2014). The economic contribution of high-growth firms: Do definitions matter? *Journal of Industry, Competition and Trade*, in press.

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

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.

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

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.

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.

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.

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.
Wennberg K., Wiklund, J., Detienne, D.R., & Cardon, M.S. (2010). Reconceptualizing entrepreneurial exit: divergent exit routes and their drivers. *Journal of Business Venturing*, 25, 361-375.

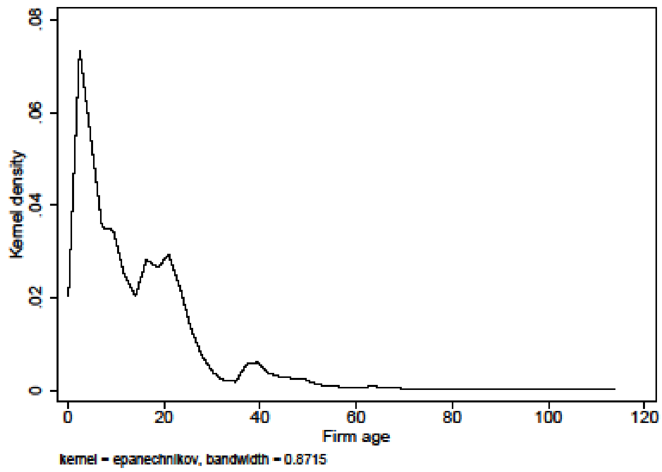

Figure 1. The age distribution of firms in 2010

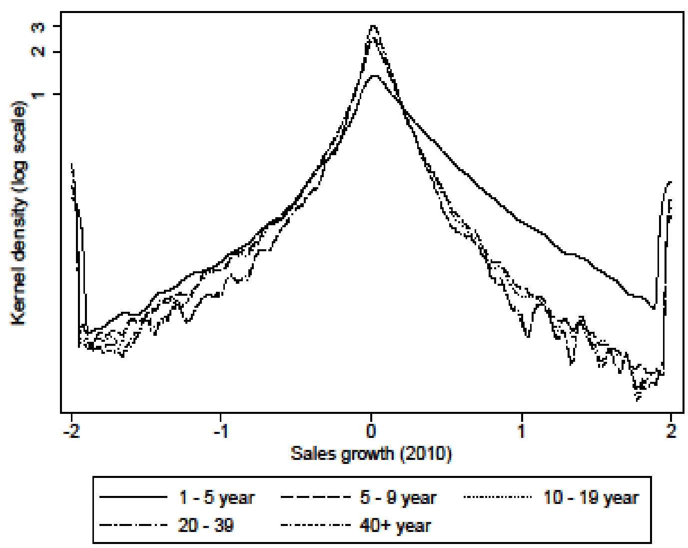

Figure 2. Kernel density plot of sales growth in 2010

Table 1. Description of sales growth by age categories

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

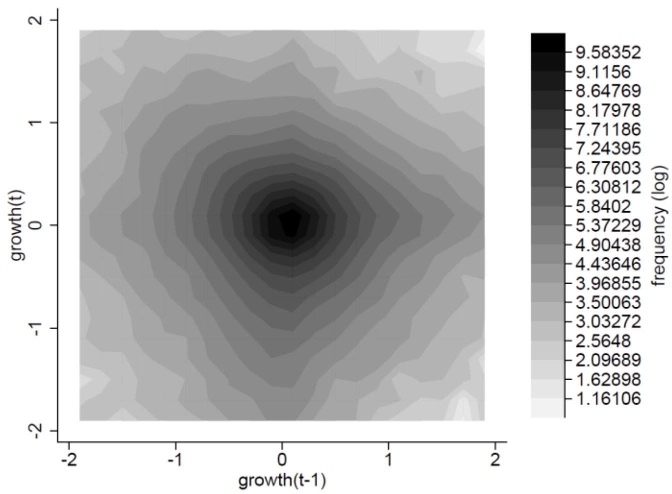

Figure 3. Contour plot for pairs of consecutive growth rates (i.e. growth(t-1) and growth(t)) in 2010 (all firms)

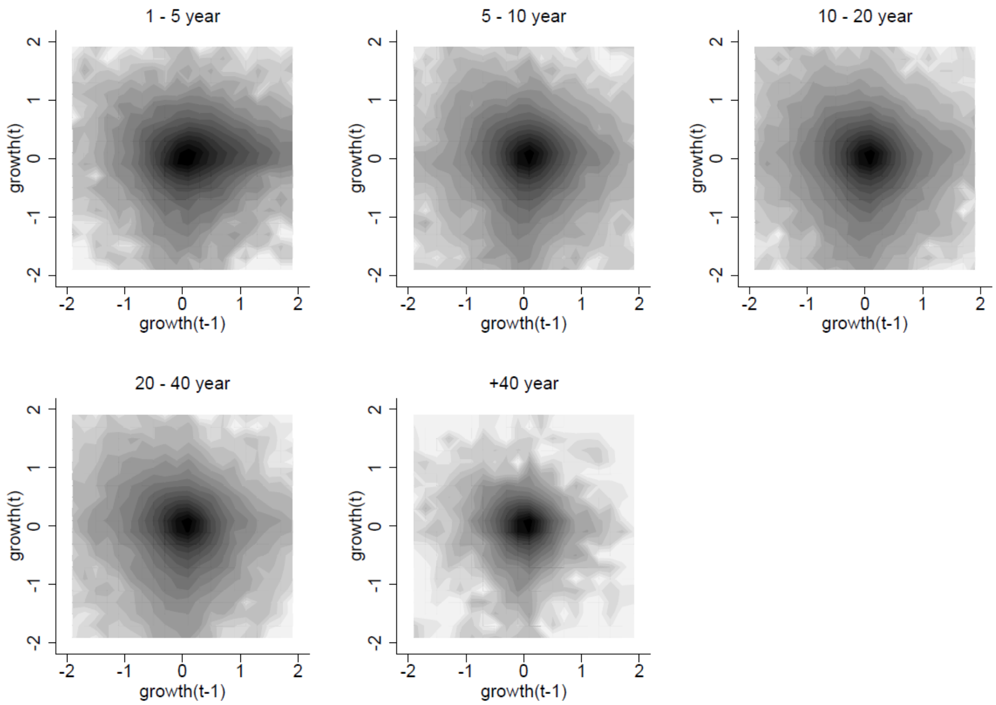

Figure 4. Contour plots for pairs of consecutive growth rates in 2010, for five age groups.

Table 2. Regression estimation of equation (3) for all firms in 2010

All firms	(1)	(2)	(3)	(4)	(5)
Sales Growth (2010)	$q = 0.1$	$q = 0.25$	$q = 0.50$	$q = 0.75$	$q = 0.90$
$L.growth$	0.010	-0.020***	-0.037***	-0.079***	-0.111***
	(0.008)	(0.003)	(0.004)	(0.005)	(0.006)
$L.\log(size)$	0.086***	0.032***	0.004***	-0.026***	-0.083***
	(0.002)	(0.001)	(0.000)	(0.001)	(0.002)
$L.\log(age)$	0.015***	-0.002	-0.011***	-0.032***	-0.042***
	(0.004)	(0.002)	(0.001)	(0.002)	(0.004)
Constant	-0.750***	-0.567***	-0.343***	-0.032	0.120***
	(0.031)	(0.029)	(0.019)	(0.029)	(0.017)
Observations	171 276	171 276	171 276	171 276	171 276
R2	0.004	0.001	0.006	0.011	0.010
Pseudo R2	0.040	0.016	0.005	0.021	0.087

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

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

Age < 5	(1)	(2)	(3)	(4)	(5)
Sales Growth (2010)	$q = 0.1$	$q = 0.25$	$q = 0.50$	$q = 0.75$	$q = 0.90$
$L.growth$	0.035***	0.012	0.004	-0.014	-0.040**
	(0.012)	(0.010)	(0.007)	(0.010)	(0.020)
$L.\log(size)$	0.102***	0.031***	-0.009***	-0.064***	-0.149***
	(0.006)	(0.003)	(0.002)	(0.005)	(0.007)
$L.\log(age)$	-0.042**	-0.029**	-0.020**	-0.071***	-0.105***
	(0.021)	(0.013)	(0.008)	(0.014)	(0.026)
Constant	-0.852***	-0.549***	-0.341***	-0.069*	0.310***
	(0.080)	(0.040)	(0.100)	(0.041)	(0.059)
Observations	18 999	18 999	18 999	18 999	18 999
R2	0.005	0.003	0.004	0.012	0.013
Pseudo R2	0.042	0.012	0.008	0.037	0.106

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

Table 4. 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)	$q = 0.1$	$q = 0.25$	$q = 0.50$	$q = 0.75$	$q = 0.90$
$L.growth$	0.034**	-0.012	-0.039***	-0.084***	-0.126***
	(0.016)	(0.008)	(0.007)	(0.010)	(0.011)
$L.\log(size)$	0.104***	0.034***	0.002**	-0.038***	-0.118***
	(0.005)	(0.002)	(0.001)	(0.002)	(0.004)
$L.\log(age)$	0.053	0.002	-0.007	-0.040***	-0.044**
	(0.033)	(0.012)	(0.005)	(0.011)	(0.019)
Constant	-1.288***	-0.869***	0.085***	0.127***	0.087**
	(0.088)	(0.035)	(0.011)	(0.034)	(0.040)
Observations	38 067	38 067	38 067	38 067	38 067
R2	0.007	0.004	0.007	0.015	0.015
Pseudo R2	0.036	0.014	0.005	0.029	0.100

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

Table 5. Regression estimation of equation (3) for firms with 9 < Age <20 years in 2010

9 < Age < 20	(1)	(2)	(3)	(4)	(5)
Sales Growth (2010)	$q = 0.1$	$q = 0.25$	$q = 0.50$	$q = 0.75$	$q = 0.90$
$L.growth$	-0.007	-0.035***	-0.053***	-0.100***	-0.133***
	(0.013)	(0.006)	(0.007)	(0.009)	(0.012)
$L.\log(size)$	0.091***	0.033***	0.004***	-0.028***	-0.086***
	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)
$L.\log(age)$	0.054**	-0.002	-0.018***	-0.050***	-0.067***
	(0.025)	(0.009)	(0.004)	(0.007)	(0.016)
Constant	-1.178***	-0.840***	-0.695***	-0.509***	-0.251***
	(0.067)	(0.037)	(0.025)	(0.017)	(0.036)
Observations	53 675	53 675	53 675	53 675	53 675
R2	0.004	0.000	0.010	0.016	0.013
Pseudo R2	0.039	0.017	0.005	0.026	0.090

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

Table 6. Regression estimation of equation (3) for firms with Age>19 years in 2010

19 < Age	(1)	(2)	(3)	(4)	(5)
Sales Growth (2010)	$q = 0.1$	$q = 0.25$	$q = 0.50$	$q = 0.75$	$q = 0.90$
$L.growth$	-0.012	-0.033***	-0.060***	-0.102***	-0.129***
	(0.014)	(0.006)	(0.007)	(0.008)	(0.010)
$L.\log(size)$	0.078***	0.030***	0.005***	-0.018***	-0.065***
	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)
$L.\log(age)$	-0.025*	-0.001	-0.002	0.004	0.035***
	(0.014)	(0.004)	(0.002)	(0.003)	(0.008)
Constant	0.185***	0.031	-0.023	-0.106***	-0.285***
	(0.059)	(0.029)	(0.020)	(0.028)	(0.044)
Observations	60 535	60 535	60 535	60 535	60 535
R2	0.001	0.000	0.008	0.010	0.006
Pseudo R2	0.049	0.021	0.007	0.026	0.082

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

AGE REGRESSIONS

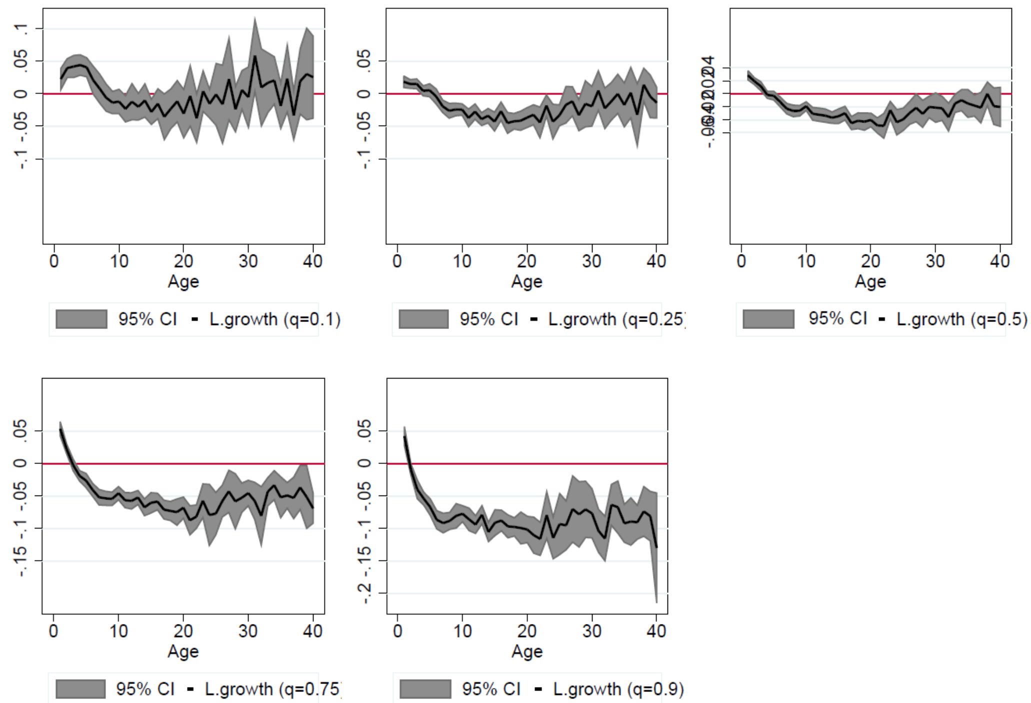

Figure 5. Quantile regression for age 1- 40. Each datapoint corresponds to an estimate of ϕ_2 from equation (3) for each year. Hence, each of the 5 plots in this Figure present 40 estimated coefficients (and standard errors) obtained from 40 regressions, one for each year.