Age, growth and diversification in the German machine tool industry, 1936-2002

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Abstract:
We focus on the relationship of age, growth and diversification patterns of German machine tool manufacturers in the post war era. Based on trade journal data our analysis reveals four main insights. Firstly, we observe that firms have lower diversification rates as they grow older, and that eventually diversification rates even turn negative for old firms on average. Secondly, we find that product portfolios of larger firms tend to be more diversified, although less than proportionally so (which suggests that larger firms are composed of larger submarkets). Thirdly, with respect to consecutive growth activities, quantile autoregression plots show that firms experiencing diversification in one period are unlikely to repeat this behavior in the following year. Fourthly, survival estimations reveal a lower hazard risk for older organizations as well as the fact that growth activities in general reduce the risk of failure controlling for various additional firm and industry specific fixed effects and business cycles. Interestingly, when differentiating between various age cohorts and their specific consequences when growing, we find that especially teenaged firms face the highest risk of failure.

JEL codes: L20, L25

Keywords: Diversification, firm growth, industry evolution, firm age

1. INTRODUCTION

A large number of papers have focused on firm growth from the perspective of Gibrat's Law, where firm size and growth can be easily quantified in terms of variables such as sales or employees. As a consequence, more qualitative features of the firm growth process have been overlooked. Relatively little is known about the empirical regularities of the modes of firm growth, regarding diversification patterns.

A major obstacle facing research on firm growth through diversification is the availability of data on the submarket portfolios of firms. While firms are required to report financial data to authorities for tax purposes, there is less interest in the product respectively submarket structure of firms. Another problem is that it is not easy to clearly delineate product classes and hence submarkets. In particular, it is difficult to compare the diversification structure of firms operating in industries that differ greatly.

In spite of these difficulties, however, some authors have focused on diversification patterns in the pharmaceutical industry, where submarkets can be defined in terms of the Anatomical Classification System (Matia et al 2004, Bottazzi and Secchi 2006). Others have delineated submarkets by using the well-known Standard Industrial Classification (SIC) codes (e.g. Teece et al. 1994, who investigate the technological relatedness of sectors).

In this paper, our approach is to focus on a specific industry over time, the German machine tool industry throughout the post war era. Based on the individual annual product portfolios, which we compiled from trade journals, we are able to distinguish between two growth modes. While growth represents an expansion of the product portfolio within the current fields of activity, i.e. a submarket, diversification takes place when a new submarket is entered. Our measure of these different growth modes is defined in terms of machine tool submarkets as defined by the trade journals classification scheme. By focusing on a specific industry, we do not attempt to generalize across all firms in all sectors, but we aim to obtain an accurate indicator of growth and diversification for the firms within this industry.

Our contribution to the literature is twofold. Firstly, research into firm growth has not been able to make much distinction between the different modes of growth that growth events entail. Nevertheless, efforts have been made to distinguish between organic and acquisitive growth (Davidsson and Delmar 2006, Lockett et al 2011). Our unique dataset allows us to distinguish between diversifying growth and non-diversifying growth, a topic which has not received much attention in the previous literature. Secondly, our study contributes to the small set of empirical investigations regarding firm growth with a special attention on product respectively submarket portfolio development and its interdependence with individual firms' age.

With the help of quantile autoregressions and survival analysis the following results were obtained: Firstly, we observe that firms on average decrease their growth and diversification rates as they age, even beyond the point where they eventually turn negative for old firms. Secondly, we find that product portfolios of larger firms tend to be more diversified. Thirdly, with respect to consecutive growth activities, quantile autoregression plots show that firms experiencing growth in one period are unlikely to repeat this behavior in the following year. Fourthly, survival estimations support the liability of newness hypothesis and further reveal that growth activities reduce the risk of failure controlling for various additional firm and industry specific fixed effects and business cycles. Moreover, teenaged firms, though not the youngest cohort, have the highest risk of failure when growing. The paper proceeds as follows. Section 2 contains a brief literature review. In Section 3 we give a short introduction to the industry setting and introduce the database before we run our analyses in Section 4. Section 5 concludes and shortly presents some discussion points and limitations of the presented study.

2. PREVIOUS LITERATURE

The burgeoning literature on firm growth has almost exclusively focused on growth in terms of variables such as employment and sales, and to a lesser extent, assets and value added (see Coad 2009 for a survey). This literature on firm growth generally takes Gibrat's 'law of proportionate effect' as a starting point for empirical investigations. A lot of attention has therefore focused on the relationship between size and growth, and in most cases (but not all) a negative relationship between size and growth has been observed, such that larger firms experience slower growth. Research has also focused on the effect of age on growth, with researchers generally finding that older firms experience slower growth.

Although this body of literature has made considerable progress in improving our understanding of the determinants and processes of growth, we argue that the definition of growth that is usually taken is rather narrow and that it fails to deal with issues relating to growth 'modes' and growth 'directions'. Firm growth should not merely be considered in terms of 'homogenous' quantifiable expansion along a continuous scale, but instead there are different 'ways' to grow; there are different 'modes' of growth, such as organic growth and acquisitive growth (Lockett et al., 2011). If firm growth is measured purely in terms of conventional variables such as sales and employees, these features of the growth process are missed.

While most work has not distinguished between organic growth and acquisitive growth (or else has focused exclusively on organic growth), Davidsson and Delmar (2006) do distinguish between these two growth modes in their analysis of Swedish firms, and observe that the share of organic growth tends to decrease with age. It has also been observed that the growth of conglomerate firms contains a higher proportion of acquisitive growth than that of single-segment firms (Maksimovic and Phillips, 2008), suggesting that there may be an element of 'acquired taste' in growth modes (no pun intended). Cefis, Marsili and Schenk (2009) observe the impact of merger and acquisition activity on industry concentration and the aggregate firm size distribution. Lockett et al (2011) observe that acquisitive growth has a positive effect on subsequent organic growth, while organic growth can act as a constraint on subsequent organic growth. This finding can be explained in terms of the firm's knowledge base: an acquisition can be seen as an influx of new resources which lead to an increase in knowledge as the firm strives to internalize these diverse resources.

Another drawback of the conventional empirical strategy concerning firm growth is that it has not investigated the 'directions' of growth, distinguishing between cases of growth in local markets versus internationalization, or (closer to the core message of this paper) growth in established product markets versus diversification into new product categories and submarkets.

We should however mention that we are not the first to focus on firm growth and diversification. Previous research has investigated the pharmaceutical industry, where submarkets can be defined in terms of the Anatomical Classification System (Matia et al 2004, Bottazzi and Secchi 2006). This submarket classification scheme sorts products into categories that are broadly based on anatomical groups, but are also categorized on the basis of chemical structure, indication, and method of action (Bottazzi and Secchi 2006, p849). These papers observe that larger pharmaceutical firms are diversified into more submarkets, although the degree of diversification is less than proportional to firm size because larger firms are composed of larger submarkets. An advantage of this methodological approach is that a detailed and meaningful indicator of diversification can be used; a drawback, however, is that the results observed for the pharmaceutical sector may not be easily generalized to other industries.

Another approach to investigate diversification patterns, focusing on a much wider range of industries, has delineated submarkets by using the well-known Standard Industrial Classification (SIC) codes. In this vein, Teece et al (1994) observe that firms appear to maintain a certain degree of coherence even as they diversify into new markets.

Our contribution to the literature is twofold. First, our unique dataset allows us to distinguish the degree of diversification in firm growth profiles, a topic which has not received much attention in the previous literature. We complement existing findings from the pharmaceutical industry with our results for the German machine tools industry, over the period 1936-2002. Secondly, our study contributes to the small set of empirical investigations regarding firm growth with a special attention on product respectively submarket portfolio development and its interdependence with individual firms' age.

3. THE EMPIRICAL SETTING & THE DATABASE

3. 1. The machine tool industry

Within our analysis we stick to the broad definition of modern machines tools being defined as power-driven machines that are used to produce a given form of a work piece by cutting, forming or shaping metal (Wieandt 1994). Besides the core processing techniques such as milling, turning, pressing, and grinding, there exists an extensive variety of special purpose machinery, which are supplied especially to highly sophisticated industries such as automobiles, aircraft, military, and computers (Ashburn 1988). Given this diverse set of customers and their individual demand, the industry is marked by a high degree of product heterogeneity with respect to size, type, complexity and functionality (Sciberras and Payne 1985). Moreover, the industry consist foremost of traditional, often family-owned, small and medium sized enterprises.

These characteristics of the machine tool market offer an interesting opportunity to investigate the development of firms' product portfolios throughout their lifetime.

3. 2. THE DATABASE

The upcoming analyses are based on a dataset, which covers the entire firm population of machine tool manufacturers in West Germany between 1936 and 2002.[1,2] The main data source for this data collection is the buyer's guide *Wer baut Maschinen*? (Who makes machinery?), which has been issued annually since the 1930s by the *Verein Deutscher Maschinen- und Anlagenbau (VDMA; Association of German machine tool producer).*

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[1] This data set was used in previous studies on regional growth patterns (Fornahl and Guenther 2011), as well as relocation and survival dynamics (Guenther 2009b, Buenstorf and Guenther 2011; Falck et al. 2010).

[2] No catalogues were issued between 1944 and 1948 as heavy machine tool production was banned in Germany until 1949.

The data source does not only allow us to identify all 2,267 firms that are active in the machine tool market after 1949, it also delivers the annual product portfolio of each individual firm as well as entry and exit timing for each of these products. In particular in accordance with the trade registries the industry can be divided into 36 submarkets, e.g. drilling, turning, or milling machines, which in turn consist again of up to 70 individual product, respectively machine tool, variations, e.g. various types of drilling machines.[3]

This hierarchical structure builds the basis for our measures of the two growth modes. In the analyses we define *growth* as the expansion of the product portfolio in terms of adding a new product variation within a submarket a firm has previously already been active in. That is, when a producers of milling machines offers a new variation of milling machines in addition to the existing set of milling machines. In contrast to growth we define *diversification* as the expansion of the product portfolio beyond the previously supplied submarkets, e.g. when the milling machine specialist also starts supplying boring machines.

As argued above next to the growth and diversification patterns within this population of manufacturers, we are also interested in its interdependence with firm age. As not all founding dates are available we use the first year in which we observe a firm within the industry as a proxy for its founding date. Even though this is only a proxy, we can be sure that we come as close as possible to the actual founding date. Given the fact that the data source is a buyer's guide firms are highly interested in advertizing their products and draw the attention to their existence in this industry-wide catalogue as soon as possible. Therefore, we do not run the risk of leaving out very young and small firms. Moreover, this circumstance makes us confident that we actually account for all products offered by each individual company. Moreover, we are able to identify the location of each company, a fact we will make use of in the survival analysis.

[3] For a detailed description of the dataset see Guenther (2009a).

A second data source (VDW 2005) was used to gather aggregated employment data. Individual annual data for sales, employees or any financial performance indicator are not available.

Before we start the analysis we will present a few summary statistics regarding the firm size distribution (Figure 1) as well as growth and diversification events (Table 1).

Figure 1 presents the firm size distribution between 1955 and 2002 based on the number of products. We differentiate between highly specialized manufacturers offering only a single product, specialized producers (2-4 products), moderately diversified firms (5-16 products) and highly diversified suppliers offering more than 17 different machine tools. We find that the average number of different products offered by firms increases between 3.65 in 1955 to 4.25 in 1970, and decreases again after 1989 from 4.11 to 3.16 in 2002. Similar to Fleischer (1997) we find that the share of highly specialized manufacturers decreases from 1955 to 1989, while at the same time the percentage of moderately diversified firms increases from 18.98% to 30.64%. After 1989 these trends were reversed and the share of highly specialized firms increased again while fewer firms (21.29%) were moderately diversified (5-16 products). Interestingly, the group of highly diversified firms continuously shrinks.

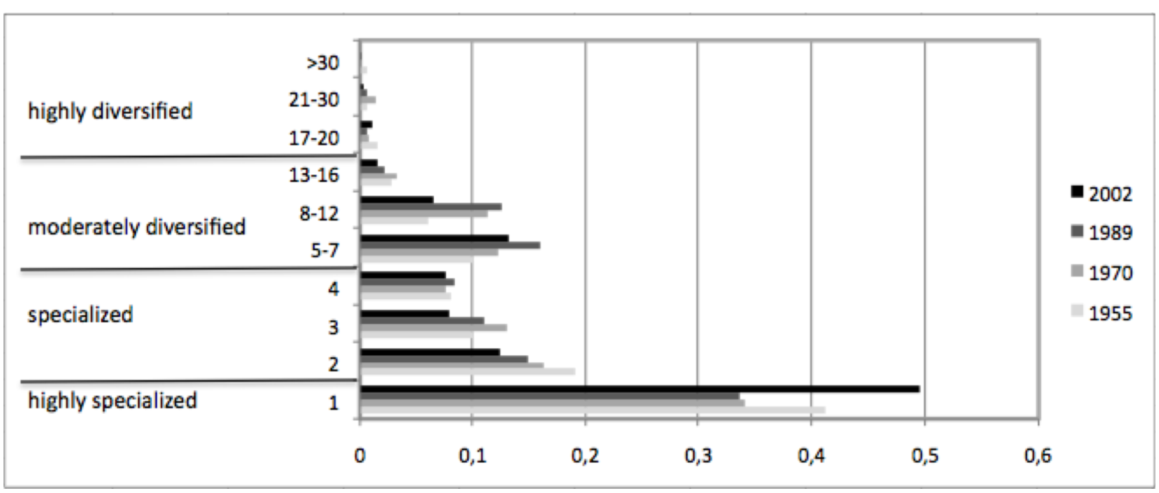

Figure 1: Firm size distribution based on the number of products, 1955-2002 (Guenther 2009a).

While Figure 1 represents only four snapshots of the industry, we will now look deeper into the dynamics within the individual product portfolios and take growth and diversification into consideration. Table 1 shows that in most cases, firms do not grow. Interestingly enough, in 320 cases we observe that firms do not grow but they do diversify. In our data, positive growth events are approximately equal in number to negative growth events, but negative growth occurs a bit more often. It is interesting to observe that in a few cases positive growth is sometimes accompanied by a *decrease* in diversification, and, conversely, that negative growth is sometimes accompanied by an *increase* in diversification. In the majority of cases, however, growth events occur without diversification.

Table 1: Summary statistics on growth events and diversification

No change	25088		
No growth but diversification	320		
Growth	7932		
of which:			
Positive growth		3579	
of which:			
no diversification			2201
increase in diversification			1322
decrease in diversification			56
Negative growth		3813	
of which:			
no diversification			2257
increase in diversification			92
decrease in diversification			1464
Total	32800		

4. ANALYSIS

4.1 AGE DISTRIBUTION

Recent work has shown that the distribution of firm ages can give interesting insights into the structure of industries (Coad 2010). Interest in the age distribution has been hindered, however, by difficulties obtaining data on the first few years of new businesses. Our dataset, however, boasts a comprehensive coverage of new firms in the machine tools industry.

Figure 2 shows the evolution of the age distribution over time, in the case of firms entering after 1960. This age distribution is of interest given that previous work has suggested that early entrants tend to have higher chances of surviving based on a first mover advantage. The age distribution tends to flatten out over time, as waves of new entrants enter in each year, but a fraction of older firms continues to survive. It is interesting to observe that the kernel density is not entirely smooth, indicating perhaps that there may be clusters of firms of a similar age.

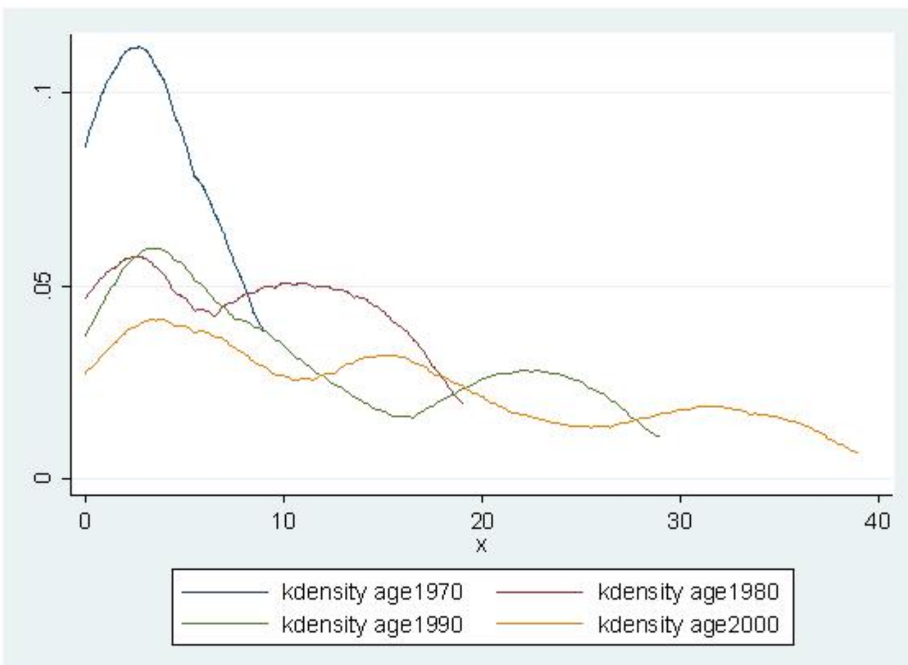

Figure 2: age distribution of firms entering after 1960

4.2 AGE AND GROWTH

In this section we consider the relationship between age and the two growth modes. Figure 3 shows how mean growth rates vary with age, where growth is measured in terms of entry into new machine variations (growth), or into new submarkets (diversification).

Given that age is usually coded as a discrete variable, rarely exceeding values of about 50, we consider it appropriate to plot our results with age as a discrete horizontal axis.[4] We focus on means, not medians, because we are not especially concerned about outliers.

Both types of growth decrease with age. It is interesting that older firms have negative mean growth rates. Although some authors seem to posit a direct positive relationship between age and size (e.g. Greiner 1972), our results caution that there is no clear relationship between age and number of submarkets. However, other work has shown that older firms do not have negative growth rates, on average (Coad, Segarra, Teruel 2010). How can these two results be reconciled? We suggest the following: older firms might put more emphasis on refocusing, and expanding within their existing product lines, rather than trying to enter new product lines and submarkets. This is consistent with conjectures that, along the life cycle, firms focus less on exploration and more on exploitation of existing capabilities.

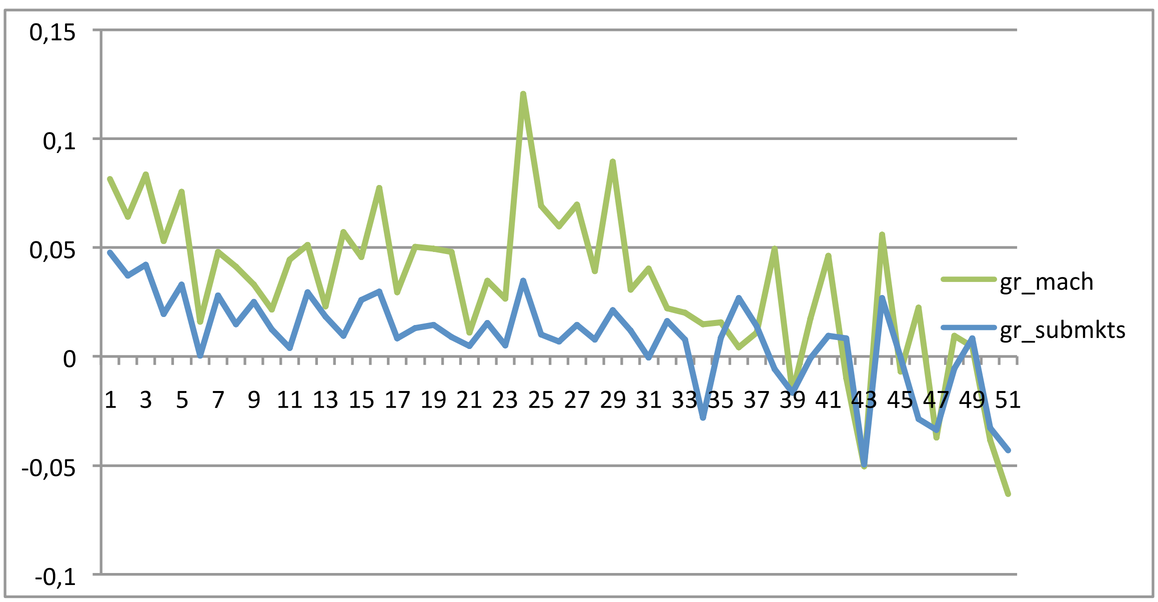

Figure 3: mean growth rates for different ages, where growth corresponds to entry into new machine variations or new submarkets

[4] Our plots therefore bear some similarity to Figures 3 and 4 in Huergo and Jaumandreu (2004).

Knowing that grwoth rates vary across age groups, we now want to investiagte in hoiw far past grwoth activities affect future growth? This issue can be addressed by performing quantile autoregressions of firm growth. Figure 4 shows that, over most of the (conditional) growth rates distribution, growth behaviour in the previous period has no effect on current growth. At the upper and lower extremes of the distribution, however, the coefficient becomes negative. If a firm experienced relatively large growth in the previous period, it is unlikely to repeat this in the current period. Given that product development cycles in this industry are rather long, i.e. between 3 to 5 years, the fact that firms do not grow continuously but rather in steps can be explained.

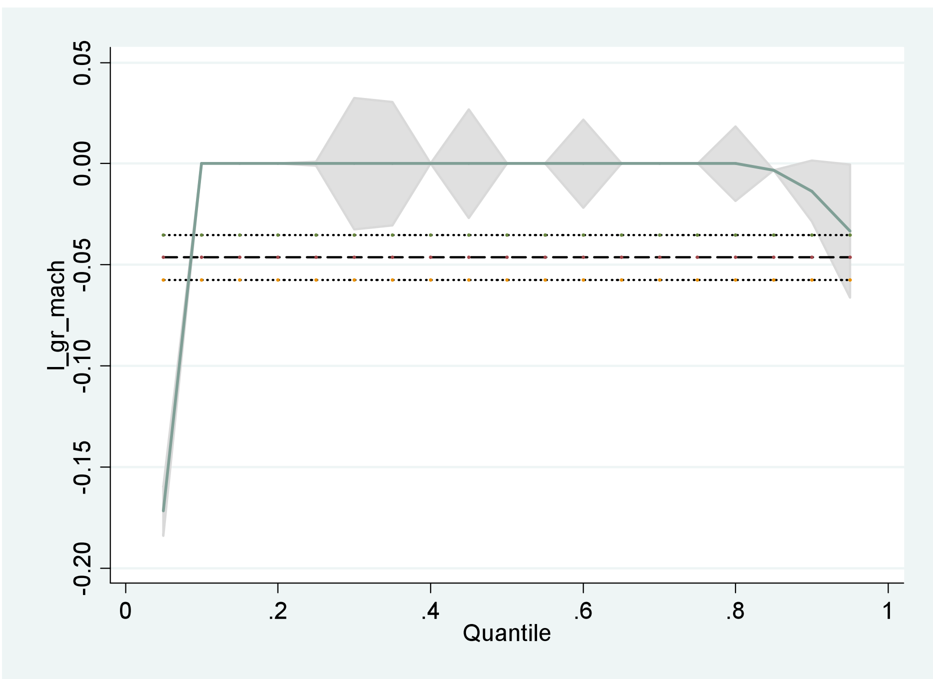

Figure 4: quantile autoregression of growth dynamics – if you grow in one period, you are not likely to grow again in the next period.

4.3 GROWTH AND DIVERSIFICATION

Our previous results, relating to our interpretation of Figure 3 above, suggest that diversified firms may have submarkets of different sizes. That is, a ‘submarket’ is not a unit of homogenous size, but may vary in size across firms.

Little is known about the structure of submarkets within firms, mainly because of data limitations. Previous work on the pharmaceutical industry has shown that total firm size and size in individual submarkets are correlated (Matia et al 2004, Bottazzi and Secchi 2006), such that growth in the number of submarkets occurs less than proportionally with respect to growth of sales.[5]

In our dataset, we can investigate how submarket size varies with firm size in the following way. We can compare total industry employment (dependent variable) with nonlinear functions of the total number of submarkets by all firms in the industry (explanatory variable) to get an idea of the evolution of the number of employees per submarket, and as a consequence to see how submarket size varies with firm size. Data on total industry employment is taken from a second data source (VDW 2005), to complement our firm-level data on number of submarkets per firm.

Our baseline regression equation in this section is as follows:

$IndustryEmpl_t = \beta_0 + \beta_1\ Submkts_t + \beta_2\ Firms_t + \beta_3\ (Submkt/Firm)_t + \beta_4\ ((Submkt^2)/Firm)_t + \varepsilon_t$

[5] In these studies, submarkets are defined in terms of different micro-classes according to the Anatomical Classification System (Bottazzi and Secchi 2006, p828).

Table 2: OLS regressions with total industry employees as the dependent variable. A constant term is always included in the regression but not reported here.

40 observations - 1950-1989							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
# firms	48,1650						
	1,47						
# submarkets		**125,6898**	**107,3923**	35,5129			
		9,13	8,50	1,89			
# subm/firm			**47988,2400**				
			4,80				
# subm2/firm				**37,1567**			
				5,40			
# machinevariations					**48,8344**	**39,3171**	18,1166
					8,37	5,89	1,37
# mach/firm						**13982,3200**	
						2,30	
#mach2/firm							**5,6945**
							2,35
Obs	40	40	40	40	40	40	40
R2	0,0311	0,6558	0,8108	0,8186	0,5859	0,6482	0,6547

In the results table above (Table 2) we investigate the determinants of total industry employment. To do so, we match industry level data (on employment) with aggregate data obtained by summing all observations per year in our firm-level dataset. These datasets do not correspond exactly, but they are closely related.

Column (1) shows that the relationship between total industry employment and number of firms is positive, but interestingly enough it is not statistically significant, and the associated R2 is very low. This is because firms vary greatly in size – simply counting the number of firms is not a good indicator of total industry employment. It is more informative to consider how industry employment varies with number of submarkets (column (2)) or number of machine variations (column (5)). These coefficient estimates are highly significant, and the R2 is considerably higher. These estimates can be improved upon, however, by taking into account the number of submarkets per firm. When firms contain many submarkets, these submarkets are likely to be larger than submarkets operated by undiversified firms. Therefore, even after controlling for number of submarkets, we see that submarkets per firm, and also submarkets^2 per firm, are significantly positively related to total industry employment (see columns (3) and (4)). Similar results hold for machine variations (see columns (6) and (7)).

Our results indicate that diversified firms are larger than undiversified firms for two reasons. First, of course, diversified firms are larger because they are active in more submarkets. Second, the individual business units of diversified firms are larger than the individual business units of undiversified firms.

These findings corroborate previous findings by Matia et al (2004) and Bottazzi and Secchi (2006) on diversification and submarkets in the pharmaceutical industry. Although data on submarkets is not easy to obtain, we use our unique dataset to show how average submarket size also increases with total firm size in the German machine tools industry.

4.4 GROWTH AND SURVIVAL

Now as we have portrayed differences in growth and diversification patterns among different age cohorts, we now turn our attention to the interdependence of growth and the survival of firms.

4.4.1 Estimation strategy

In the upcoming analysis we will thus investigate whether growth is systematically accompanied by an increase in survival chances. The analysis will be conducted in three steps. First of all we will test whether the size as such is related to the risk of failure. Secondly, we will investigate in how far age and growth affect the likelihood of survival, more specifically whether growth at different ages has a different effect on future survival. Lastly, we analyze whether there is a tendency to be observed that firms downsize during the last years before they exit the market.

To analyze these three sets of estimations we apply the following simple proportional Cox hazard model (Cox, 1972):

$$h_i(t) = h_0(t)\, exp(\alpha_e + \alpha_r + \alpha_t + \alpha_p + \beta_1 x_{i1} + \beta_2 x_{ik} + \cdot \quad \cdot \quad \cdot + \beta_k x_{ik})$$

with $h_i(t)$ being the hazard rate, i.e. the risk of failure, at time t of firm i conditional on a set of k firm-specific (time-varying) covariates $x_{i1}, \ldots, x_{ik}$. $h_0(t)$ represents an unspecified baseline hazard function. All models include α_e , α_r and α_p , i.e. a set of dummies specifying the entry cohort, the location and the product portfolio of firm i further specified below.

α_e is a set of dummies differentiating all active producers in the machine tool industry between 1949 and 2002 according to their first year of observation, their entry timing. These dummies allow for entry-cohort specific variation within the baseline hazard. Accordingly, we define α_r, α_p and α_t as region-specific, product-specific and year specific dummy variables in order to account for varying baseline hazards within regions, individual products, and individual years. Thereby, we can capture all observed and unobserved effects that are due to agglomeration externalities or industry-specific time trends such as product and industry lifecycle as well as business cycles respectively.

Throughout the estimations we account for the fact that not all firms exit within the observation period, i.e. they do not experience a failure event and are thus right censored.

For the upcoming analysis the following information was extracted from the data source introduced in the very beginning of the paper:

Survival: For each individual firm we track its overall survival time being defined as the time between the first and last year of observation within the machine tool industry.[6]

[6] Unfortunately, we cannot control for M&As as an exit mode as opposed to bankruptcy.

Given that the industry as well as firms existed already before the beginning of our observation period in 1949, we are aware of the fact that firms might have already been exposed to the risk of failure before we start the analysis. In order to account for this we redefine our age variable as follows.

Age: The age of a firm is approximated by using the year of the first observation within our analysis timeframe as the founding date. Using the additional catalogues of the data source from 1936 until 1943, we are able to include this information and correctly account for the additional years of existence before the observation period of our analysis starts.

Size: is defined as the number of machine tool variations a firm produces in the respective year. Accordingly:

Growth: a firm grows if it increases (decreases) the number of machine tool variations *within the same submarket* from one period to the next; thus, growth is defined as the difference between the number of machine tool variations at time t and the number of machine tool variations at time t-1.[7]

In order to avoid an omitted variable bias in our survival estimations, we control for various effects, which are known to affect the survival chances of firms in general:

1. All models include regional fixed effects at the level of regional planning districts. Thereby, we can at least partly control for the unobserved heterogeneity of different locations and their influence on the survival chances of the individual firm.
2. We include year fixed effects (of 5-year intervals) in order to take care of the unobserved heterogeneity due to business cycles as well as the industry life cycle as such.
3. We differentiate between five entry cohorts in the industry to account for the possibility of a first mover advantage phenomenon respectively for the

[7] Within this preliminary survival analysis we do not consider the second growth mode, i.e. diversification.

heterogeneity of founding conditions of each cohort; the five cohorts are defined as follows: (1) entry <1960; (2) 1960<=entry< 1970; (3) 1970<=entry< 1980; (4) 1980<=entry< 1990; (5) entry>= 1990.

4. We moreover control for the type of manufactured products per year as the survival might not only depend on the amount of products produced, respectively the size of the firm, but also on the actual type of product considering its individual product life cycle.

4.4.2 Results

In our baseline Model 1 (see Table 3) we are interested in whether the size of a firm as well as its age in general influence the firm's risk of failure. As described above we control for regional and year specific fixed effects as well as entry cohorts and the type of products for each firm and each year. The negative coefficients indicate that being larger and older results in a significantly higher future life expectancy as the hazard risk is reduced by each additional product respectively year.

Model 2 extends the baseline model by including a growth effect, i.e. we investigate whether on top of the level effect of size there are additional hazard reducing effects to be witnessed for firms that extend their product portfolio. As expected, growth further reduces the risk of failure.[8]

In Model 3 we further differentiate between different age cohorts in order to test for the commonly observed non-linear but inverted u-shaped relation between age and risk of failure, i.e. the liability of newness and adolescence hypotheses (Bruderl and Schussler, 1990). In our data tough we do find evidence for the increased risk of failure for young firms, but as Model 3 shows growing older is accompanied by a reduction in the hazard risk throughout all age cohorts.

In Model 4 we analyze if the hazard reducing effect of growth activities is observable for all age cohorts, i.e. we test if firms of all ages benefit equally from growing (on top of the level effect we see for size as such). Therefore, we include interaction terms for all age cohorts, with the youngest age cohort serving as the reference group. And indeed, we do

[8] The number of observations and subjects is reduced from Model 1 to Model 2 as those firms are dropped in Model 2 that survive less than two years, and consequently no growth activities can be recorded.

see a moderating effect of these interaction terms. Interestingly, teenaged firms have an even higher risk of failure when growing as compared to the youngest group of firms, even though teenagers are not the group with the highest growth rates. But as firms grow older, the interaction terms eventually become negative, and growth activities increase firm survival rates. Thus, not all age cohorts benefit equally from growing in terms of reduced hazard rates, and particularly surviving puberty seems to be a risky challenge.

Table 3: Survival regressions, applying a Cox proportional hazards model

	Model 1	Model 2	Model 3	Model 4
Size	-.162***	-.154***	-.153***	-.157***
	(.023)	(.025)	(.025)	(.025)
Age	-.020***	-.019***		-.019***
	(.005)	(.005)		(.005)
Growth		-.047*	-.047*	-.019
		(.027)	(.027)	(.053)
agecohort2			-.376**	
			(.147)	
agecohort3			-.637***	
			(.173)	
agecohort4			-.757***	
			(.120)	
agecohort5			-.891**	
			(.232)	
agecohort2*growth				.120*
				(.062)
agecohort3*growth				-.003
				(.077)
agecohort4*growth				-.122**
				(.062)
agecohort5*growth				-.053
				(.074)
Regional FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
Enrty cohort FE	yes	yes	yes	yes
product type FE	yes	yes	yes	yes
subjects	1931	1691	1691	1691
failures	1564	1346	1346	1346
Log pseudolikelihood	-10193,368	-8573,923	-8571,649	-8567,75

Note: Standrad errors (adjusted for clustering by firm) are shown in parentheses

***** ≤ 0.01; ** ≤ 0.05; * ≤ 0.10**

5. CONCLUSION

We look at the age, growth and diversification of German machine tool manufacturers, 1949-2002, using data concerning product registration in trade journals. We observe that firms have lower growth and diversification rates as they grow older, and even that old firms have negative diversification rates on average. Moreover, we find that firms have different submarket sizes, and larger firms appear to be composed of larger submarkets. Quantile autoregression plots show that firms experiencing growth are unlikely to repeat this behavior in the following year. Lastly, survival estimations reveal that growth activities in general reduce the risk of failure controlling for various additional firm and industry specific fixed effects and business cycles. But when differentiating between different age cohorts we find that teenaged firms face the highest risk of failure when growing. Firms at the very beginning of their life cycle also increase their hazard risk when growing, but to a lesser extent. When firms are older than 30 though, growth activities significantly reduce the risk of failure.

Of course our analysis has some limitations. We do not only consider just one single industry, and thereby cannot generalize from our conclusion, but we also only use a proxy for age. Despite these obvious drawbacks of our study, we nonetheless think that it is worthwhile pursuing further investigations based on this setting. Future studies may explore growth directions of firms in more detail. For example, do firms prefer to grow within existing product categories, such that they only diversify into new product categories once all the diversification possibilities within the existing family of products are exhausted? Does this pattern differ for young and old firms? A second set of questions could be based on the technological relatedness of the submarkets firms decide to diversify in. Do firms choose technologically closely related submarkets when diversifying, or do they spread the risk even broader over relatively unrelated submarkets. Again the differentiation between the growth strategies of young and old firms would be insightful as well as the combination with further survival analyses to gain a deeper understanding of the special risks teenaged firms face.

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