ARE GAZELLES MORE INNOVATIVE THAN OTHER FIRMS?

WERNER HÖLZL AND KLAUS FRIESENBICHLER (WIFO)

Werner Hölzl  
Austrian Institute of Economic Research  
PO box 91  
A-1103 Wien  
Austria  
Tel.: +43-1-7982601-472  
Mail: Werner.Hoelzl@wifo.ac.at
1. INTRODUCTION

Fast growing SMEs are recognised as a central source of dynamism in modern developed and developing economies. The special role of fast growing SMEs is also increasingly recognised by policymakers. Over the past 20 years economic policies across Europe and other countries have implemented support measures aiming to foster the emergence of fast growing SMEs. Many of the policies that have been implemented are targeted towards the high-tech segment of the economy, which is considered to provide high potential for extraordinary growth.

However, despite the importance observers attribute to gazelles, knowledge about high growth firms is surprisingly limited. Buss (2002) goes as far as to state that the phenomenon of "emerging high growth firms has been virtually ignored in the professional literature". One of the reasons may be related to the fact that the state of being a gazelle is usually a temporary phenomenon in the life of a company. Some firms settle down to become average sized firms, some become large firms, and others fail and disappear.

The research on gazelles in the ongoing INNOVATION WATCH – SYSTEMATIC project of DG Enterprise attempts to provide evidence on the innovation behaviour of gazelles. Our goal is to provide some representative evidence based on the Community Innovation Survey dataset. The key research questions are:

- Are gazelles more innovative than other firms?
- Is the cooperation behaviour of gazelles different from the cooperation behaviour of average firms?
- Do gazelles perceive innovation obstacles differently than average firms?
- Do gazelles use different strategies to protect their innovations?

In this paper we provide a first snap-shot of the results of this research on gazelles. We primarily focus on the first research question, where we want to establish whether gazelles are – as commonly assumed – more innovative than other firms.

One should keep in mind that the evidence presented in this paper is preliminary, and the results come with a caveat:

We have not yet been able to access the safe room at EUROSTAT in Luxembourg in order to work with the CIS micro data. Our results are based on micro-aggregated data. Thus they draw on a limited dataset in terms of countries and available variables. However, we are confident that our main results are quite robust, even though we have not applied any systematic robustness checks.

This paper is structured as follows: in the next section we provide a short overview of the CIS data we use to study the innovation behaviour of gazelles. In section 3 we provide a short literature survey on firm growth and innovation, and also present stylised facts on the distribution of growth rates, as well as a discussion about different indicators of firm growth. In section 4 we present our results regarding the innovation behaviour of gazelles, which we have obtained by matching estimators and quantile regressions. Section 5 provides an outline for further research that we intend to do, and section 6 briefly summarises and discusses our results.

2. The Community Innovation Survey

2.1 What is the CIS?

The Community Innovation Survey (CIS) is a firm level survey conducted every 4 years by EU member states as well as several other non-EU countries (e.g. Norway, Iceland). The CIS aims to provide a sound source of statistical data on innovation by using a stratified sample of companies: sampling rates differ across countries, and the stratification of the sample (by size-class and sector of activity) should ensure that the samples are representative.
Since 2000, the CIS has also become a major data source of the “European Innovation Scoreboard”. Moreover CIS data are increasingly being used as a key data source in the study of innovation at the firm level in Europe, Canada and Australia (e.g. Mairesse and Mohnen, 2002).

Four waves of the innovation survey have been carried out. We use the third survey (CIS3) in this study because it is the most recent CIS available for a large number of countries. CIS-3 covers innovation activity over the period 1998-2000.¹

CIS surveys of innovation are often described as ‘subjective’ because they ask individual firms directly whether they have been able to produce an innovation and to estimate the share of sales that could be ascribed to new or significantly improved products. The assessment of the innovative character of a particular activity is at least partially dependent on the views of the performer. However the evidence provided by Mairesse and Mohnen (2004) suggests that the subjective measures appear to be consistent with more objective measures of innovation, such as the probability of holding a patent and the share in sales of products protected by patents.

2.2 What kind of data do we use in this paper?

We aim to get access to the micro data for 17 countries at the safe centre of EUROSTAT in Luxembourg. Due to delays we have not yet been able to access this data. Hence, the empirical analysis in this report uses two types of CIS data:

- **Anonymised CIS-3 micro data** that is provided by Eurostat. This dataset offers wide coverage of EU member states and allows us to control for national and sectoral differences in the factors that are relevant for innovation and performance. However, there are two drawbacks to this approach: First, data are only available for a limited set of EU member states, with a number of large and medium-sized countries missing (France, UK, Italy, Poland, the Netherlands, Sweden, Austria). Second, the anonymisation method applied by Eurostat limits the analytical potential and reduces the number of available observations significantly. In particular, the data for employment is only available in terms of size classes, thus the "Birch Index" – our preferred indicator for the selection of gazelles cannot be used. Moreover, missing data on turnover reduces the set of countries from 17 to 5 (Belgium, Czech Republic, Germany, Slovak Republic and Spain).

- **CIS-3 micro data for Austria** provided by Statistik Austria and CIS-3 data for Germany.² This data is used to calculate the results based on the Birch index.

2.1 Advantages and Disadvantages of the CIS data

The main advantage of the CIS data is that it contains detailed information on the innovation behaviour at the firm level in much greater detail than in other datasets. Thus, CIS data provides the possibility to study the innovation behaviour of gazelles in a differentiated and detailed way.

The main drawback of the CIS data is that it is a cross sectional dataset. Analysing gazelles, time-series data would allow us to examine further questions, such as, for instance, which fraction of gazelles continues to grow fast, or which role the life cycles of firms plays in the gazelle phenomenon (we cannot look at the previous growth performance of gazelles).

A second drawback of the CIS data is that it contains no financial information at all. Thus, we are not able to say anything about the question of whether gazelles grow fast because they are already more

¹ CIS-4 is already available at the national level. However, CIS-4 is not yet available in microaggregated form from EUROSTAT, nor has it been possible to access the data at the safe room in Luxembourg. As soon as CIS4 data is available for research we will extend our analyses to CIS4 data.

² We thank Christoph Grimpe of ZEW for running our statistical analyses on German CIS-3 data.
profitable than the average firm, or whether they grow fast in order to achieve above average profitability.³

Third, although it is the goal of the CIS to provide comparable innovation data for European countries, the country coverage varies substantially depending on the indicators considered. For example, the Austrian CIS-4 questionnaire does not ask for information that would allow us to construct growth rates.

3. What do we know about firm growth and gazelles?

3.1 Innovation as a main determinant of firm growth

There is an enormous amount of literature on firm growth, examining growth determinants across many dimensions (for literature reviews, see for instance Scherer and Ross, 1990; Sutton, 1997; Santarelli et al, 2006). It is widely acknowledged that the determinants of firm growth are largely idiosyncratic to the firm, the entrepreneur and the firm's position in its life cycle. For instance, access to financial resources and the entrepreneurs’ ability to recognize and exploit opportunities are very important at the earliest stages of a fast growing firm’s life cycle. Autio et al. (2007) emphasize that innovation-driven firms are established in order to pursue an identified technological opportunity. In contrast, the value of management techniques and the ability of the entrepreneur to delegate become more and more important when a firm reaches a critical size.⁴

The wide variety of determinants that is often specific to the firm or to the entrepreneurial team that sets up the firm are very difficult to measure, and even luck can play a role. As these determinants seem to be at least partly independent of each other, economists tend to look at firm growth as a process that is by and large random and largely independent of the size of the firm. In fact, most studies find that there is a high persistence of firm size dynamics, which indicates that the dynamic of the growth processes of most firms is quite limited.

However, a large number of studies have found that growth is strongly influenced by the characteristics of the entrepreneur and the firm. For example, there is now ample evidence to suggest that financing constraints are reduced by the human capital and experience of the entrepreneur (e.g. Cressy, 2006; Harabi, 2006).

But are gazelles innovative? By definition, gazelles outperform average industry growth in a Schumpeterian sense: they newly combine existing input factors and thus produce an innovation that enables them to outperform the market. When examining firm growth, Penrose (1995) placed emphasis on the importance of internal processes of change, while she also pointed out that the firm’s positioning in its industrial environment is crucial. Hence, growth is driven by ‘productive opportunity’, i.e. the interaction between the firm’s (internal) productive base and (external) market opportunities. To sustain growth potential, she pointed out that firms must permanently adjust their activities to the shift in market opportunities, which is due to changes in technologies and markets (Garnsey et al, 2006). Similarly, Bares et al (2006) find that the innovation of gazelles is their ability to deliver products quickly and be flexible in adapting and altering new technologies as well as mastering financial management.

The profile of a gazelle’s innovativeness differs across sectors according to the respective technological regimes. Gazelles are innovative in a Schumpeterian sense because they create a new market while destroying an existing one (Schumpeter mark I). On the other hand, Gazelles are likely less important in technology regimes when these foster “accumulative knowledge” (Schumpeter mark II). However, Gazelles may induce regime change: Gazelles change regimes by replacing incumbents us-

³ Recent evidence on the relationship between growth and profitability suggests that the aggregate relationship between growth and profitability is very weak (e.g. Coad 2005, Bottazzi, Secchi and Tamagni 2006).

⁴ This is confirmed by recent findings which suggest that differences in management account for approximately 30 to 40 % of the sustained wide variation in productivity between firms which is observed even in narrowly defined industries (Bloom and von Reenen 2006, Griffith, Haskell and Neely, 2006).
ing a competitive advantage – either technological or organisational – which allows them to compete on a basis other than price (Rigby et al, 2006; Slaughter, 1996). Thus, they contribute to a change in technology patterns by exploiting major knowledge, technological or market discontinuities. In both cases, gazelles are the successful bearers of technological change, either through product innovation, changes in the production process or modifications of the organisational structures.

New products play a key role in this process of economic renewal. If they meet sufficient demand, they often create new markets such as, for instance, the frozen potato industry, the PC or the software industry (Rigby et al, 2006). There is vast literature which finds that innovating firms are not only more productive (e.g. Wieser, 2001), but also grow faster than non-innovators. Often, a positive effect of innovations on profit margin effect is larger than the growth effect, but in most studies the “likelihood of growing” increases with product innovation (e.g. Geroski – Machin, 1992; Roper, 1997; Freel, 2000) or product or process diversification (e.g. Bares et al, 2006; Harabi, 2003). Applying quantile regressions to four sectors with fast changing technologies, Coad and Rao (2006) find that innovation is of much greater importance to “high-flyer” companies than to average ones.

R&D and innovation are generally acknowledged as the key drivers of firm performance (e.g. Autio et al. 2007). However, comparing gazelles to other firms, there seem to be differences in innovation success rather than differences in innovation inputs.

Although often treated as synonymous with innovation output, R&D refers to innovation input, which frequently differs from innovation output (e.g. new products, processes or patents). At the same time, successful innovation does not necessarily equal innovation input or output. This is why it has been difficult for researchers to find a direct relationship between R&D activity, such as, for instance, R&D staff or expenditures, both differing to accounting standards (Ahn, 2003), and firm performance (e.g. Klomp and van Leeuwen, 2001).

A reason for these difficulties could be that firms have specific capabilities, which complement their R&D activities and are difficult to measure. Furthermore, there may be significant lags between market success and R&D efforts – aiming at both technology development and converting the new technologies into production processes.

The development process can be split up into three different stages, with the likelihood of success at each phase determining the overall probability of innovation success. Whether to engage in R&D or not is a function of how likely it is that the technical goals will be met, the perceived probability that the innovation output will be commercialised and, third, the demand conditions and capability of a firm to commercialise the results (Coad – Rao, 2006; Mansfield et al, 1977). Furthermore, the evolution of technologies occurs erratically, which renders R&D efforts even more risky, as unpredictable development increases the risk of missing market opportunities or investing in the wrong projects. After all, some research projects’ failure to produce marketable output is simply due to bad luck.

Another frequently used innovation indicator is patenting activity, which is by definition related to inventiveness, and based on a relatively objective and stable standard that focuses on the novelty and potential utility of the patent (Ahn, 2003). However, even when patent statistics and patent citation indices are publicly available, the obtained results can be distorted, because the propensity to patent varies across countries, industries, technologies and firms (Archibugi et al, 1992). In our examination of gazelles, we found gazelles to be a cross-country and cross-sectoral phenomenon (see next section). Hence we refrained from applying an arbitrary control for these variations, and deemed patents to be an inadequate innovation indicator.

3.2 Firm growth and gazelles

Presuming gazelles to be successful innovators, we now look at the definition of gazelles, and at how their growth rates are distributed. Recent research about the growth rate distribution, which we will review below suggests that high growth is infrequent. This fits well into the research tradition initiated by Birch (1987), which shows that only a small number of small firms grow very fast. These “gazelles” account for the bulk of the overall job generation (e.g. Schreyer 2000; Hölzl 2006), and thus significantly contribute to economic growth. But how do we identify high growth firms in our work?
3.2.1 Gazelle definition

Typically two principle criteria are used for defining a firm as a gazelle. The firm must be an SME at the base year, and it must display above average growth in a specific period.

Hence, for the purposes of our study we use two definitions of gazelles:

- For the micro-aggregated data, we use the log growth rate of the turnover \( g(x) = \ln(TURN_{i,2000}) - \ln(TURN_{i,1998}) \), where \( TURN_{i,x} \) is the deflated turnover of firm \( i \) in year \( x \). The gazelles that we select are the top 10% growth firms. We did not use an SME definition due to insufficient information on employment, but we excluded all firms that underwent mergers, acquisitions and sales of business lines.

- For the (Austrian) microdata, we calculated the Birch index \( m = (x_{i,t} - x_{i,t_0}) \frac{x_{i,t}}{x_{i,t_0}} \) and selected the top 10% of performers that had fewer than 250 employees (SME definition) and again excluded all firms that underwent mergers, acquisitions and sales of business lines.

3.2.2 Descriptive statistics

Applying these gazelle definitions to the micro-aggregated CIS 3 data, we find gazelles in all Innovation Watch - Systematic sectors. However, the gazelle count reveals slight differences in the number of gazelles found across sectors. For instance, the data shows that approximately 15% of all firms in both ICT manufacturing and ICT are gazelles, whereas in food or energy we find fewer high growth firms (circa 6%).

However, the more observations there are in the respective sector, the greater the convergence of the percentage of high growth SMEs towards the chosen threshold of 10% (see table 1).

If we move the threshold of our gazelle definition to 5%, we obtain a similar picture at the sectoral level. The number of gazelles reduces it by roughly one half, i.e. if we use the upper half of the distribution of high growth firms we obtain an analogous reflection of the former picture with respect to the higher threshold for being a gazelle.

A similar picture can be drawn when looking at the gazelle count at the country level. While finding that approximately 17% of all Slovakian and about 14% of all Czech firms are fast growing, we find that a bit more than 5% of all German firms belong to the high growth segment (table 2). However, Spain, which accounts for more than half of the data, exhibits almost 10% of all identified gazelles. Again, one could presume that the higher the number of observations, the more the share of gazelles approaches the selected 10%.

Interestingly, we find that at the country level the deviation from the chosen threshold does in fact decrease with a more stringent gazelle definition of the top 5% growers. Only Germany stands out as an exception, with its share of firms classified as gazelles reaching only two percent. However, the share of high growth firms in all other countries approaches the 5% limit of the pooled distribution of growth rates for all countries.

---

5 In the scoping paper (Hölzl 2006) Gazelles were defined as the 5% top performers during a specific interval of time and selected on the basis of the Birch index of firm growth. For the final report we will use this definition and also apply the stricter 5% selection criterion. We did not use the Birch index because no employment data is recorded in the microaggregated CIS data.

6 The log growth rate is the logarithm of the growth factor. The advantage of the logarithmic scale is a correction for heteroscedasticity which comes at the price of a lower variance of growth rates. To put the values we are talking about into perspective: A value of 2 indicates that the firm is 7.3 times larger than at the beginning of the period.
The overall picture of the gazelle count reveals small country and sector related differences. However, the results do not allow us to draw conclusions about industry and country related differences in the salience of high growth SMEs. Looking at the descriptive statistics, one could presume that an increase in the number of observations fully levels out country and industry effects. In order to approach these differences more technically, we calculated an ANOVA (analysis of variance), in order to test whether the differences in firm growth can be explained by industry and country effects (see table 3).

For the ANOVA we use four different growth indicators that differ in terms of their underlying dimensions. The first growth indicator is the logarithmic growth rate. The second (third) growth indicator is the growth rate of the deviation of log turnover from the logarithmic country (industry) mean of turnover. The fourth definition refers to the change in the deviation of the logarithmic turnover to the log mean by industry and country. This removes country and industry effects, as Table 3 shows. For all four indicators, both industry and country effects appear to explain little. A decomposition of the growth variance into firm and country effects provides significant results, but they explain merely 4% of the overall variance. Put differently, country and industry effects and their interaction provide almost no explanation for differences in growth rates.

Table 1: Gazelle distribution at the sectoral level

<table>
<thead>
<tr>
<th>Sector</th>
<th>Other firms</th>
<th>Gaz.</th>
<th>Gaz. in %</th>
<th>Other firms</th>
<th>Gaz.</th>
<th>Gaz. in %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Automotive</td>
<td>492</td>
<td>66</td>
<td>11.8%</td>
<td>515</td>
<td>43</td>
<td>7.7%</td>
</tr>
<tr>
<td>Chemicals</td>
<td>600</td>
<td>38</td>
<td>6.0%</td>
<td>620</td>
<td>18</td>
<td>2.8%</td>
</tr>
<tr>
<td>Energy</td>
<td>256</td>
<td>15</td>
<td>5.5%</td>
<td>264</td>
<td>7</td>
<td>2.6%</td>
</tr>
<tr>
<td>Food</td>
<td>937</td>
<td>57</td>
<td>5.7%</td>
<td>967</td>
<td>27</td>
<td>2.7%</td>
</tr>
<tr>
<td>Machinery</td>
<td>832</td>
<td>87</td>
<td>9.5%</td>
<td>882</td>
<td>37</td>
<td>4.0%</td>
</tr>
<tr>
<td>Textiles</td>
<td>948</td>
<td>83</td>
<td>8.1%</td>
<td>988</td>
<td>43</td>
<td>4.2%</td>
</tr>
<tr>
<td>ICT</td>
<td>850</td>
<td>159</td>
<td>15.8%</td>
<td>924</td>
<td>85</td>
<td>8.4%</td>
</tr>
<tr>
<td>ICT Manufacturing</td>
<td>248</td>
<td>43</td>
<td>14.8%</td>
<td>271</td>
<td>20</td>
<td>6.9%</td>
</tr>
<tr>
<td>ICT Services</td>
<td>602</td>
<td>116</td>
<td>16.2%</td>
<td>653</td>
<td>65</td>
<td>9.1%</td>
</tr>
<tr>
<td>Other Manufacturing</td>
<td>5135</td>
<td>504</td>
<td>8.9%</td>
<td>5410</td>
<td>229</td>
<td>4.1%</td>
</tr>
</tbody>
</table>

Source: Micro-aggregated CIS 3 data (Eurostat), Wifo calculations

Table 2: Gazelle distribution at the country level

<table>
<thead>
<tr>
<th>Country</th>
<th>Other firms</th>
<th>Gazelles</th>
<th>Gaz. in %</th>
<th>Other firms</th>
<th>Gazelles</th>
<th>Gaz. in %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Belgium</td>
<td>627</td>
<td>53</td>
<td>8.5%</td>
<td>656</td>
<td>24</td>
<td>3.5%</td>
</tr>
<tr>
<td>Czech Republic</td>
<td>1504</td>
<td>206</td>
<td>13.7%</td>
<td>1601</td>
<td>109</td>
<td>6.4%</td>
</tr>
<tr>
<td>Germany</td>
<td>1726</td>
<td>92</td>
<td>5.3%</td>
<td>1781</td>
<td>37</td>
<td>2.0%</td>
</tr>
<tr>
<td>Spain</td>
<td>5540</td>
<td>549</td>
<td>9.9%</td>
<td>5816</td>
<td>273</td>
<td>4.5%</td>
</tr>
<tr>
<td>Slovakia</td>
<td>637</td>
<td>108</td>
<td>17.0%</td>
<td>699</td>
<td>46</td>
<td>6.2%</td>
</tr>
</tbody>
</table>

Source: Micro-aggregated CIS 3 data (Eurostat), Wifo calculations

Table 3: ANOVA (Analysis of variance); decomposition of the variance of selected growth indicators into country, industry and interaction effects

| Turnover growth (logarithm) | Turnover Growth (log country mean) | Growth Turnover (log industry mean) | Turnover growth (country and in- |
3.3 The distribution of firm growth rates

Gibrat’s law is the starting point of many economic studies on firm growth. It states that the rate of growth of a firm is independent of the firm’s size, and therefore has no influence on the firm’s growth in subsequent periods. It is established that Gibrat’s Law is not fully consistent with the empirical evidence. While it seems to hold when comparing established firms, the extensive international evidence that has emerged on the patterns of firm growth reveals that smaller and younger businesses, which are located at the tail of the size distribution, experience wider variations in growth rates than do larger, more mature firms (e.g. Sutton 1997, Caves 1998). This implies that the variance of growth rates of firms is not independent of their size, but diminishes with it. However, the empirical evidence is vast, and because of different methodological approaches and samples, studies are often hard to compare, resulting in great variance in the results (Santarelli et al, 2006).

Recent research on the distribution of firm growth rates shows that these do not follow a normal distribution, which further challenges Gibrat’s law. Starting with the contribution of Stanley et al. (1996) a number of studies (e.g. Bottazzi and Secchi 2003a, 2003b, 2006, Reichenstein and Jensen 2005) have established a tent-shaped distribution of logarithmic growth rates. Their results hold for a large number of countries and different levels of disaggregation. This evidence on the distribution of growth rates also provides very interesting insights on Gazelles.

Let us first consider one of these graphs in detail. Figure 1 displays the growth rate distribution of firms in the manufacturing sector for five countries over the period 1998-2000. The construction of the Figure is explained in Box 1.

The x-axis gives the log growth rate, and the y-axis depicts the probability density on a log scale. Each dot in the diagram is based on a binned frequency histogram. For each bin we calculated the density and the average growth rate in the bin. The higher the value on the vertical axis, the more firms will exhibit the assigned growth rates. The peak of the “tent” is around zero, i.e. most firms do not grow.

Box 1: Arriving at the tent-shaped distribution of firm growth

We calculate the growth rates as the first difference of normalized log size according to

$$g_i = \ln(TURN_{i,2000}) - \ln(TURN_{i,1998})$$

Source: Micro-aggregated CIS 3 data (Eurostat), Wifo calculations"
where $TURN_{i,2000}$ is log size measured in real turnover or employment in the year 2000 and $TURN_{i,1998}$ is log size in the year 1998. Based on the growth rates, we binned the growth rates to construct a binned frequency diagram. The bin size we used is between 0.20 and 0.10 depending on the size of the sample. Based on the binned frequency distribution we calculated the implied density distribution. Each dot in one of the growth rate distribution graphs represents one of the bins. We plot it using the calculated density and the mean growth rate in the respective bins. This is the empirical distribution of growth rates.

Next we follow Stanley et al. (1996) and Bottazzi et al. (2003b) by fitting a Laplace distribution, that gives us the tent-shaped pattern in the figures. The Laplace distribution has the following density distribution:

$$f(x) = \frac{1}{2b} e^{-\frac{|x-a|}{b}},$$

where $a$ is a location parameter and $b$ is a shape parameter. The density distribution of the Laplace distribution is reminiscent of the normal distribution; however, whereas the normal distribution is expressed in terms of the squared difference from the mean $\mu$, the Laplace density is expressed in terms of the absolute difference from the mean. Consequently, the Laplace distribution has fatter tails than the normal distribution. We estimate the two parameters using well known Maximum-Likelihood estimators:

$$\hat{a} = \tilde{x}_{0.5}; \quad \hat{b} = \frac{1}{n} \sum_{i=1}^{n} |x_i - \tilde{a}|,$$

where $\tilde{x}_{0.5}$ is the sample median. This procedure does suit our needs, as it shows a good fit of the empirical distribution with the Laplace distribution for all sectors.

Bottazzi and Secchi (2003a, 2003b, 2006) and other researchers (e.g. Fagiolo et al, 2006) go further and estimate a more general and flexible family distribution in order to account for the robustness of their finding. They use the exponential power distribution, also known as the Subbotin distribution, which includes the Laplace and the Normal distribution as particular particular cases. However, estimating this general distribution is not easy, as (i) the Maximum Likelihood estimator is known to be biased in small samples and (ii) the optimisation problem is not analytic.

Moving to the left or to the right on the x-axis, one can see much lower density values on the y-axis. This means that few firms grow or decline strongly. Gazelles, defined as the ten percent of firms with the highest turnover growth rates, are found on the far right side of the distribution.

Figure 2 displays the firm growth rate distribution (turnover) across the different systematic sectors. The plots show that each of the sectors is quite well characterized by the tent-shaped distribution. Figure 3 displays the firm growth rate distribution across the manufacturing sectors for the 5 countries for which we have data. Again, the Laplace distribution fits the growth rate distributions remarkably well. Figure 4 shows the growth rate distribution for employment, turnover and apparent labour productivity (turnover per employee) for Austria.

The evidence that growth rates are characterized by a tent-shaped distribution is remarkably robust. The tent-shape of the growth rate distribution appears at the aggregated level (pooling of countries and sectors) as well as at the disaggregated level (country or sector). Interestingly, even the ICT service and ICT manufacturing sectors show that most firms have quite modest growth rates. This is surprising as the time period we are looking at is 1998-2000, the peak of the ICT boom. Hence, even in times of a ‘speculative bubble’ and the associated ‘speculative growth’, most companies do not grow. In fact, the highest density is always registered for growth rates around nil.
Figure 1: Growth rate distribution of turnover for the manufacturing sector of the 5 countries.

Source: Wifo calculations

This evidence is not limited to our sample of CIS data, but is also found for disaggregated and aggregated analyses of the Italian manufacturing sector (Bottazzi and Secchi 2006), for Danish firm data (Reichenstein and Jensen 2005) and US data (Stanley et al. 1996, Bottazzi and Secchi 2003).

Figure 2: Plot of logarithmic firm growth rates and logarithmic frequencies across the systematic sectors

Source: CIS 3 micro-aggregated data, Wifo calculations

Figure 3: Plot of logarithmic firm growth rates and logarithmic frequencies at the country level
Overall, the available evidence suggests that:

- The choice of turnover, employment or value added as growth indicators seems to make little difference to the shape of the growth rate distribution, even if the parameters change.

- In accordance with the stylised facts of growth rates, the fattest tails are recorded for the employment growth indicator, because employment is a variable characterised by a higher degree of 'lumpiness' than other growth indicators. Adjustment costs are particularly high for employment and growth. Furthermore, employment is more likely to reflect relatively large events, such as, for instance, the opening or closing of plants. This is unaffected by the results of Delmar et al (2003) which show that there is a low contemporaneous correlation between the extent of turnover, employment or value added as growth indicators seems to make little difference to the shape of the growth rate distribution, even if the parameters change.

- It does not matter whether we consider or exclude firms that grow or decline through mergers or sales of parts of the enterprise. The tent-shaped pattern remains and fits the data remarkably well.

- The available evidence suggests that the tent-shaped distribution of growth rates is relatively independent of the time considered and the level of aggregation. The tent-shaped distribution of growth rates is found whether one looks at the manufacturing sector as a whole or at single sectors, provided that the number of firms is large enough. Only with longer time horizons (e.g. 7 years) does the shape of the distribution begin to change towards a distribution that is equally close to the Laplace and the normal distribution. Bottazzi and Secchi (2006) explain this on the basis of a central limit theorem. However, they do not find any evidence that this distribution converges to the normal distribution.\(^7\)

---

\(^7\) Recent research even suggests that the time series of aggregated country growth rates follow a tent-shaped growth rate distribution (Fagiolo et al. 2007).
3.4 What are the implications of a tent-shaped distribution of firm growth rates?

Tent-shaped distributions are an empirical regularity. From a statistical point of view, this distribution of firm growth rates on a logarithmic scale, which is well approximated by a Laplace distribution, provides evidence that the tails are fatter than Gaussian ones.

However, from an economic point of view, this evidence suggests that corporate growth is driven by relatively frequent and relatively "big" events that cannot be accounted for with normally distributed shocks. After having established that the tent-shaped distribution of growth rates seems almost ubiquitous, let us discuss the implications for gazelle research:

- We find gazelles in every sector, both in high and low tech industries. This implies that the phenomenon of gazelles is primarily an economic one, and not a technological one. In fact, most studies find that only a third of all gazelles are high tech companies (see Rigby et al., 2006). High growth often comes from innovative approaches to marketing or organisational structures, for example Red Bull or Starbucks (Rigby et al., 2006). Above average growth rates not only root in the use of new technologies, but also in changes of organisational routines (Nelson and Winter, 1982). Similarly, Bares et al. (2006) argue that gazelles have the ability to achieve capabilities of cost reduction and quality improvements through greater organisational flexibility. Furthermore, gazelles use incremental innovation rather than radical innovation, since radical innovation is linked to high R&D expenditures, which require resources smaller firms do not have.

- Most firms have very low growth rates most of the time. This suggests that gazelles are better than other firms at exploiting opportunities and creating competitive advantages by launching new products, introducing new services, realising organisational changes, etc. Gazelles seem to be quick in reacting to market trends and implementing adjustments in their strategies. (Rigby et al., 2006; Bares et al., 2006)

- Gazelle counts per se are problematic for a number of reasons. First, a mere gazelle count is more of an indicator of discontinuities than of sectoral growth. Second, the impact gazelles have differs across sectors, depending on how they change the respective sectoral market...
dynamics. Third, since gazelles are by definition a key element of economic change, gazelle counts cannot contribute to forecasts about technological development or growth at the sectoral level. Thus, gazelle counts by sector or country using cross-section data are probably not always a useful measure of gazelle activity. For most gazelles high growth is a temporary phenomenon, and longitudinal data might provide greater insight into the beginning and the end of the growth process in light of the life cycle of the firm or its products.

3.5 Why do we observe a tent-shaped distribution of growth rates?

An important question to ask is why we observe such a tent-shaped distribution of growth rates. A stylised fact that is supported by the tent-shaped growth rate distribution is that most firms do not grow. Firm growth is affected by a number of factors, such as technology, the micro- and macroeconomic environment including regulation, institutional factors at regional or sectoral level, and – most prominently – firm-specific determinants. But why is the peak of the “tent” around zero regardless of whether we look at expanding or declining sectors? Several explanations attempt to explain this phenomenon.

The easiest answer to why most firms do not grow is to note that many entrepreneurs do not desire growth. For instance, there seem to be differences in growth ambitions in the reasons for starting a business (push or pull factors; ‘lifestyle’ owners), ownership structures (e.g. family businesses with no growth ambitions are sometimes labelled “gophers”), the age of the entrepreneur (younger entrepreneurs tend to put greater focus on growth) and so forth (e.g. Bridge et al, 2003). Furthermore, some studies find not only resistance to change, but also the inabilities of managers to be a major growth impediment (e.g. Hay and Kamshad, 1994). However, even if this evidence holds for some firms, it does not provide a general explanation for the massive concentration of firms at low growth rates.

An economic explanation that might provide some insight is related to adjustment costs, i.e. the costs that emerge from the reallocation of production factors due to a change in firm size. It is a stylised fact that the expansion of firms in terms of capital or investment is “lumpy” at the firm level. Adjustment costs and uncertainty provide an explanation as to why we observe this at the micro-level, and why aggregated patterns are much smoother. The explanation is based on the fact that growth is associated with fixed costs, which are independent of the extent of the adjustment. Empirical evidence supports this view. For example, Doms and Dunne (1998) find for the US that on average 25 % of a plant’s cumulative investment over a 17-year period occurs in a single year.

However, standard adjustment costs are unlikely to contain the whole story. First, the fat tails should be less fat, and we should observe a much faster convergence of the growth rate distribution towards a normal distribution if adjustment costs alone could provide an explanation. In fact, Bottazzi and Secchi (2006) offer an explanation that reproduces the empirical pattern of a Laplace distribution of growth rates, based on a simple stochastic model of firm growth. Bottazzi and Secchi (2006) start from an “island model” in the tradition of Simon. That is they assume a finite number of business opportunities to firms. All firms, operating in a number of submarkets, take up available opportunities. Bottazzi and Secchi (2006) modify this model and assume that the way firms search for new solutions of opportunities is characterised by cumulative and self-reinforcing mechanisms, as argued by Arthur (1994). In their model they capture this by assuming that new opportunities for firms depend on the number of opportunities that the firm has already caught. This can also be interpreted as representing the fact that firm-specific capabilities play an important role in the exploitation of growth opportunities. In their simple model growth is triggered by firms entering into new submarkets, i.e. they exploit market opportunities through product diversification, for which they use knowledge that they must either acquire or already possess (cf. also Dosi et al. 2000). This suggests that high growth firms should be more successful in launching new products. If we assume that (new) knowledge is a significant driver of firm growth, no matter whether it has been produced in-house or acquired from an external source – this leads to the hypothesis that gazelles should - compared to other companies - have a substantially higher fraction of products that are new to the market or new to the firm. Diversification need not be restricted to innovation activities and product diversification; entering new submarkets can also be associated with selling the products to new customers located further away (i.e. exporting). Thus gazelles should be characterized by higher export growth than other firms.
Economic theory provides a number of reasons for why firms export and why they concentrate on local markets. However, most of these studies discuss the relationship between firm size and exports, and not between exports and growth (Bonaccorsi, 1992). Arguments on why exports improve firm performance are numerous. For instance, exporting firms serve a larger market, and thus they are able to realise economies of scale and scope, which again result in greater efficiency in the production process. Second, they do not fully depend on national markets, and can smother negative home market volatility if market trends are anti-cyclical. Put differently, the diversification of target markets renders their portfolio less prone to local demand volatility. Third, only productive and innovative firms can afford the extra costs of selling abroad. Moreover, exporters are exposed to fiercer competition, and therefore have to improve their capabilities more quickly than nationally operating companies. Then again, there are several arguments against the hypothesis that exports are contributors to the growth of SMEs. These are for instance limitations in resources (e.g. managerial, financial etc.), limited scale economies and restrictions in export management abilities, or a higher risk perception than that of larger firms (e.g. Wagner, 2002; Bernard – Wagner, 1997).

The vast empirical literature has produced somewhat mixed results on the link between growth and exports and innovation and exports at the firm level. Our discussion might reverse the often presumed causality that exports lead to firm growth. This would mean that entrepreneurial success leads to higher exports, because successful firm concepts search for new markets. In such a situation, firms either start to export after reaching critical size, which allows them to cope with internationalisation, or they go international in order to achieve an ‘optimal’ size that allows them to experience the above-mentioned benefits (Hirsch – Bijaoui, 1985 or Cassiman – Martinez-Ros, 2007).

4. Methods and results

4.1 Introduction

McKelvey and Andriani (2005) insist that management studies should look at extreme values rather than rely on Gaussian statistics. Most statistical methods analyse the deviation of the mean behaviour and not the behaviour of „outliers”, which is of greater significance when analysing single firms.

Examining gazelles, we face the same problem: in fact, we analyse systematic differences between gazelles, a number of outliers and other firms. We cope with this problem by using two different methodologies:

- First, we apply a matching estimator. We identify gazelles, and then we select from the control group (all other firms that are not gazelles) observations that are similar to gazelles in our base year 1998. The selection criteria we applied for similarity refers to firm characteristics such as, for instance, firm size, export intensities, and sector and country classifications. Comparing gazelles with their 1998 “twins” using non-parametric t-tests avoids the problem of comparing apples with oranges.
- Second, we apply quantile regressions. These allow us to uncover whether variables exert a constant influence across the conditional distribution of growth rates or not. For instance, we explore if the fraction of products that are new to the market are more important for high growth firms than for average companies, or even for firms that barely grow.

4.2 Descriptive statistics and the matching estimator

Before looking at how the matching estimator that we applied works in greater detail, let us first have a look at a number of structural and innovation indicators (Table 4).

\[^{8}\text{For instance, Cassiman – Martinez-Ros (2007) provide a literature review on empirical results on innovation and exports. Lefebvre – Lefebvre (2000) also provide a survey that focuses on the innovation characteristics of exporting firms.}\]
A comparison of innovation indicators for gazelles and other firms shows that high growth firms do not seem to differ in terms of their sheer number of product or process innovations. About a third of all firms started to operate a new or significantly altered process, and approximately 38% launched at least one new product.

Gazelles’ research intensities, however, seem to be higher than for other firms. Their R&D per turnover ratio is 22% higher than the research intensity for other firms that are not identified as gazelles. Furthermore, when one looks at indicators of innovation success, gazelles seem to be remarkably different. As expected, their turnover shares of products new to the firm, is significantly higher than the 10.4% of other firms, reaching 14.2%. The same holds for products that are new to the market. Non-gazelles realised approximately 3.7% of their turnover with such products, while the turnover of top 10% growth firms consisted of products that are new to the market of almost 7%. This is almost twice the value as for other firms. Furthermore, this pattern does not change substantially if we choose a 5% growth threshold for gazelles.

Given these results, one could say that their innovation behaviour is not dramatically different to that of other companies, while their innovation success is quite different. However, such ‘aggregate’ statistics might be misleading due to factors that are specific to the firm that we have not controlled for. Furthermore, simple descriptive statistics or t-tests compare firms without any information, observing whether they are similar or not. For instance, Table 4 describes means of samples that are on the one hand comprised of high growth firms that are supposedly SMEs and on the other hand of all other firms (large established enterprises, small family businesses etc.).

Table 4: Means of innovation indicators for gazelles

<table>
<thead>
<tr>
<th></th>
<th>Other firms</th>
<th>Gazelles</th>
<th>Other firms</th>
<th>Gazelles</th>
</tr>
</thead>
<tbody>
<tr>
<td>R&amp;D over turnover</td>
<td>0.9%</td>
<td>1.1%</td>
<td>0.9%</td>
<td>1.3%</td>
</tr>
<tr>
<td>Process Innovation</td>
<td>32.1%</td>
<td>30.0%</td>
<td>30.3%</td>
<td>32.0%</td>
</tr>
<tr>
<td>Product Innovation</td>
<td>38.4%</td>
<td>38.5%</td>
<td>38.3%</td>
<td>39.3%</td>
</tr>
<tr>
<td>Turnover of products that are new to the firm</td>
<td>10.4%</td>
<td>14.2%</td>
<td>6.7%</td>
<td>8.4%</td>
</tr>
<tr>
<td>Turnover of products that are new to the market</td>
<td>3.7%</td>
<td>6.9%</td>
<td>3.8%</td>
<td>7.6%</td>
</tr>
<tr>
<td>Observations</td>
<td>10034</td>
<td>1008</td>
<td>11042</td>
<td>489</td>
</tr>
</tbody>
</table>

Assuming that firm specificities are similar among firms that share certain characteristics, we try to avoid the problem of comparing apples with oranges by applying a matching estimator. This means that instead of simply comparing two groups of observations with each other, matching procedures reduce one group to “statistical twins”, thus rebuilding an experimental dataset.

Matching estimators were designed to examine the effect of a treatment. Since we use observational data, i.e. data that is not randomised, and furthermore identify a subset of the sample as being treated, there is no ‘treatment effect’ as discussed in the literature. However, by applying a matching estimator, we control for the characteristics that affect both the quasi-treatment and the response (de Luna – Waernbaum, 2004). We deem gazelles to be the ‘treatment variable’, thus using the matching estimator as a tool that produces sophisticated statistics on differences of high growth to similar firms.

For each high growth firm, we identified two firms that are statistically almost alike in a number of criteria. These ‘covariates’ are:
The firms that we chose are based on exact matches of the 2-digit Nace classifications and of the same country. This avoids the problem of comparing firms that act in different sectoral or national environments.

The control group is further selected on the basis of size (turnover; employment for Austria), whether they are part of an enterprise group, the export intensity (exports over turnover in 1998) as a proxy for the firms' internationalisation, and where the most significant market is (regionally, nationally etc.)

We use organically growing firms only, i.e. we excluded firms that were growing through mergers and acquisitions.

For each gazelle we select two firms in the control group (non-gazelles) and then test whether the two sets of firms are different over a number of innovation variables by means of a t-test. Figure 4 illustrates how statistically alike firms that are denoted by an ‘x’ are matched, i.e. how gazelles are assigned to firms as similar as possible. Other companies, denoted by a ‘y’, are naturally not considered in the comparison.

Figure 4: The basic idea of matching

Implementing matching estimators, one has to make an assumption about whether the reaction of firms on the treatment is heterogeneous or not. We assume this to hold, i.e. we expect that the effects differ between firms, and thus implement an average treatment effect for the treated estimator (Blundell – Costa-Dias, 2002).

We use nearest neighbour matching that estimates the (quasi) average treatment effect on an independent variable. Put differently, we look for differences between each gazelle, which is the (quasi-)treatment, and two similar firms (non-treated) in innovation (dependent) variables. The nearest neighbour matching first computes the differentials of the values of the covariates and, drawing on these results, then assigns similar observations of the treated to the nearest opposite treatment. We then estimate the average difference between the “observed” and the “potential” outcome (for a detailed discussion of the method see Abadie et al (2004) or Abadie and Imbens (2006).

In econometric theory, multidimensional covariate matching estimators are often biased due to the dimensionality problem. Propensity scores improve the quality of matching estimations by reducing this problem. Therefore, matching procedures based on propensity score have recently gained popularity among researchers. However, we were not able to use propensity score matching methods, as these methods do not allow for ‘exact matching’ and we found that the propensity scores estimated using our covariates were not particularly informative. Instead, we decided to use exact matching specifications for the country and sector covariates. This ‘exact matching’ requires a covariate estimator like the nearest neighbourhood method that we applied.
Yet, being aware of possible distortions due to dimensionality, we use a bias adjusted method by correcting for the differences within the matches for the differences in the covariate values. We then enter the adjustment of all matching covariates linearly in the regression function, and estimate an OLS function. Furthermore, we estimate heteroskedasticity-consistent standard errors using four matches in the second matching stage, i.e. across observations of the same treatment level. Notably, in this second procedure of estimating the standard errors we used four matches - a higher number to further improve the bias correction than we used in estimating the (quasi-)treatment effect, where we worked with two matches (Abadie et al, 2004).

Summarising the matching estimator, we use the following procedure:

1. Identification of the top 10% growth firms
2. Choice of the covariates, i.e. the matching criteria:
3. ‘Matching’ of two statistically similar firms according the selection criteria
4. Comparison of the firms in the two samples over several innovation variables

4.3 Results of the matching analysis

The innovation indicators that we use in the matching estimators are all from the CIS survey. We study different kinds of innovation indicators that are relevant at different stages of the innovation process. We consider R&D intensity as input into the innovation process, using the presence of innovation activities and the degree to which the innovations are done in-house as characteristics of the innovation process. In addition we use a set of indicators of innovation output: the introduction of new process, product and organizational innovations. Innovation success is measured by the fraction of turnover of products new to the firm or new to the market. We also look at whether gazelles experience stronger export growth than do similar firms.

All these indicators are from the CIS 3 questionnaire. While some of the indicators are readily available, we construct the indicator for organisational innovation from the answers to the question whether the firm introduced new management techniques or concepts, introduced or significantly altered firm strategies, and whether new organisational structures were introduced.

The indicator ‘own innovation’ is based on the answers whether product and/or process innovations were developed by the firm alone or in collaboration with other firms and institutions.

Table 5 provides an overview of the results obtained from the matching estimations. The coefficients that describe the difference between gazelles and similar firms are above the p-values and the significance stars for significance levels of 99% (***) 95% (**) and 90% (*). Our findings display great variance across sectors and countries. Here we will concentrate on the results for the entire manufacturing sector and on a striking difference between the results of the two R&D indicators that we employ.

We find no significant difference between gazelles and similar firms in R&D intensities, measured by R&D per turnover. However, the Austrian micro-data allows us to construct an employment-based R&D intensity indicator, which is positively significant. Although employment and turnover growth are to some extent correlated, they seem to be related to different processes (e.g. Delmar et al, 2003). Turnover is more volatile, and relative turnover increases are naturally much bigger than relative employment increases. As our gazelles are in the top 10 % of growers in terms of turnover, R&D expenditures have a large short-run fixed cost component and the R&D intensity is measured ex post, this result should not be that surprising. Measuring R&D intensity in terms of R&D expenditures per employee would provide more insight into the issue whether gazelles are more R&D intensive than other firms. In fact, as the results for Austrian Manufacturing industries show, if we use such an indicator then gazelles have a higher R&D intensity, even if gazelles are identified by a birch index based on employment growth. Yet note that when we change the gazelle definition, we are likely to select quite a different set of firms.

Gazelles seem to be slightly more innovative when one looks at the introduction of new processes. A similar picture could be drawn with the indicator of new products. Although this result is statistically in-
significant, it is close to the 90% threshold. They are also more innovative in changing their organizational structures.

As expected, gazelles are more successful at introducing products to the market. Gazelles are successful first movers rather than imitators, as the insignificant result of the turnover share of products that are new to the firm suggests. The innovation of gazelles is more likely to be developed by the firm than by other companies and more likely to be adopted. This means that gazelles are rather “stand alone” innovators. However, this does not imply that they are less co-operative in their innovation behaviour than other similar firms. Preliminary results suggests that there is no significant difference in the cooperation behaviour of gazelles.

The strongest result that we find is that export growth is a major determinant of high growth firms. Gazelles increase their exports more than do similar firms which are not growing as fast. This can be explained on the basis of the fact that in the case of gazelles we look at the transition process from being a small firm to becoming a bigger firm. The results we obtain are supported by Cassiman – Martínez-Ros (2007), who find for Spanish firms that successful product innovation is a very important driver of export activities. They also find that the decision to start exporting is positively influenced by product innovation in the previous year.

4.4 Quantile regression

The evidence from the matching analysis shows that gazelles are more innovative in a large number of features than are similar firms. However, this does not provide the full picture. Therefore we employ quantile regression in order to analyse the determinants of gazelle behaviour. Following the bulk of the literature on firm growth, we use an augmented Gibrat’s Law equation to study the determinants of the innovation behaviour of gazelle firms. The Gibrat’s law equation we use is the following:

$$ g_i = \alpha + \beta_1 S_{i,t-1} + \beta_2 \text{INN}_i + \beta_3 \text{CON}_i, $$

where $g_i$ is the growth rate indicator (growth rate or Birch index) for firm $i$, $\alpha$ is an intercept, $S_{i,t-1}$ is the firm size at time $t-1$, $\text{INN}_i$ is a vector of innovation indicators for firm $i$, $\text{CON}_i$ is a vector of control variables and $\beta_1$, $\beta_2$ and $\beta_3$ are the respective coefficient vectors.

As the empirical evidence suggests, the explanatory power of such regressions is usually quite low, and it is found that Gibrat’s Law is rejected for small firms (e.g. see Sutton 1997 for a review). Nevertheless such a formulation is useful, as it is often used in the literature.

Attention has not only been placed on size as a factor of firm growth but also on issues such as management quality, ownership status and advertising or innovation expenditures. However, as Geroski (2000) remarks, although the estimated coefficients are often statistically significant, their explanatory power is remarkably weak. There are a number of studies beginning with Scherer (1965) which show that innovation has a positive effect on firm performance. For example, using a sample of 539 quoted UK firms, Geroski and Machin (1996) observe that innovative firms grow faster than do non-innovators. Coad and Rao (2006) show that innovation is more important for fast growing firms.

In our analysis we use 6 different indicators of innovativeness:

1. Own innovation (owninno) an index that gives the weight of 1 to innovations that were developed in-house, a weight of 0.5 to innovations that were developed in collaboration with partners and a weight of 0 to innovations that were bought from other firms.
2. R&D intensity is measured by R&D expenditures over turnover
3. Organizational innovation: an index based on the answers to the questions whether the firm introduced new management techniques or concepts, introduced or significantly altered firm strategies and whether new organisational structures were introduced.
<table>
<thead>
<tr>
<th>Indicator</th>
<th>Manufacturing gr-turn</th>
<th>Micro-aggregated data (DE, ES, BE, CZ, SK)</th>
<th>Austrian micro data</th>
</tr>
</thead>
<tbody>
<tr>
<td>R&amp;D int. (turnover)</td>
<td>-0.002 (0.89)</td>
<td>-0.002 (0.34)</td>
<td>0.13 (0.768)</td>
</tr>
<tr>
<td>R&amp;D int. (empl.)</td>
<td>0.069 (0.01)**</td>
<td>N.A N.A N.A N.A N.A N.A N.A N.A N.A N.A</td>
<td>(0.05)** (0.02)**</td>
</tr>
<tr>
<td>Own innovations</td>
<td>0.073 (0.55)</td>
<td>0.0820 -0.05 0.22 0.09 0.24 -0.001 0.1 0.05 0.23</td>
<td>(0.76) (0.30)</td>
</tr>
<tr>
<td>Organizational</td>
<td>0.016 (0.29)**</td>
<td>N.A N.A N.A N.A N.A N.A N.A N.A N.A N.A 0.05 0.23</td>
<td>(0.76) (0.30)</td>
</tr>
<tr>
<td>Innovation</td>
<td>0.007 (0.55)</td>
<td>0.09 0.06 0.01 0.03 0.03 0.03 0.03 0.03 0.03 0.03 0.03</td>
<td>(0.76) (0.30)</td>
</tr>
<tr>
<td>Persistent innovator</td>
<td>0.016 (0.29)**</td>
<td>0.12 0.05 0.15 0.15 0.15 0.15 0.15 0.15 0.15 0.15 0.15</td>
<td>(0.76) (0.30)</td>
</tr>
<tr>
<td>Turnover of products new to the firm</td>
<td>0.007 (0.31)</td>
<td>0.02 0.02 0.02 0.02 0.02 0.02 0.02 0.02 0.02 0.02 0.02</td>
<td>(0.18) (0.08)*</td>
</tr>
<tr>
<td>Turnover of products new to the market</td>
<td>0.034 (0.0)***</td>
<td>0.02 0.02 0.02 0.02 0.02 0.02 0.02 0.02 0.02 0.02 0.02</td>
<td>(0.18) (0.08)*</td>
</tr>
<tr>
<td>Product innovation</td>
<td>0.03 (0.12)</td>
<td>0.12 0.03 0.11 0.05 0.18 0.006 0.03 0.13 0.07 0.13 0.07</td>
<td>(0.34) (0.67)</td>
</tr>
<tr>
<td>Process innovation</td>
<td>0.056 (0.82)</td>
<td>0.11 0.11 -0.05 0.078 -0.02 0.06 0.12 0.15 0.12 0.15 0.15</td>
<td>(0.34) (0.67)</td>
</tr>
<tr>
<td>Export growth</td>
<td>0.474 (0.00)***</td>
<td>0.575 0.573 0.23 0.52 0.75 0.51 0.44 0.47 0.11 0.47 0.11</td>
<td>(0.00) (0.541)</td>
</tr>
</tbody>
</table>

Table 5: Results from the nearest neighbour matching, p values in parentheses.
4. TURNIN: fraction of turnover that is due to products new to the firm

5. TURNMAR: fraction of turnover that is due to products new to the market

6. Innovation Cooperation: A dummy variable indicating whether the firm has any innovation cooperation with external partners.

As control variables we use:

1. Firm size in 1998 (TURN98),
2. GP, which is a dummy variable that indicates whether the firm is part of an enterprise group or not,
3. EXPINT98: the export intensity in 1998, and
4. Pavitt industry taxonomy dummies.

The evidence provided and reviewed in section 3 of this paper reveals that firm growth rate distributions are generally Laplace distributed. This distribution exhibits fat tails when compared to a normal distribution, indicating a different firm behaviour at both ends of the distribution. This suggests using a different econometric method than those methods usually employed when studying firm growth, which target average behaviour (cf. Reichenstein et al. 2006). The great advantage of a quantile regression is that it enables us to consider the entire distribution of firm growth.

Compared to OLS regression, quantile regressions provide a more “complete” story of the relationship between variables. As the name quantile regression suggests, it is not limited to regress against averages, and hence it is not limited in its explanatory value, since it also uses information that it obtains from the underlying distribution of growth rates (Koenker 2005). Quantile regressions have two major advantages when compared to OLS:

1. Quantile regressions allow us to analyse differences in the relationship between the endogenous and exogenous variables at different points of the conditional distribution of the dependent variable. That is, rather than focusing on a specific moment of the distribution, the linear quantile regression is a statistical method that allows us to study the whole range of values of the dependent variable. Quantile regressions allow us to study how one specific quantile of particular interest is correlated with a set of explanatory variables. Extending this analysis to a large number of quantiles, quantile regression allows us to examine how the partial correlation changes across the quantiles. This provides an understanding of the entire shape of the distribution and how it may be shaped by the explanatory variables.

2. The coefficient estimate for the exogenous variable is interpreted in a similar fashion as OLS regression coefficients, namely as the marginal change in the dependent variable due to a marginal change in the exogenous variable conditional on being on the p-th quantile of the distribution. Changing estimated coefficients with varying quantiles is indicative of heteroskedasticity issues (Koenker 2005).

3. Estimates of the quantile regression are more robust than those of the ordinary least square regression, where the mean value of the dependent variable is predicted. This is especially true in the presence of outliers as well as for distributions of error terms that deviate from normality.

4.5 The results of the quantile regressions

The results of the quantile regressions are represented in Figure 5. The horizontal axis of the diagrams represent the quantiles. The vertical axis represents the estimated coefficients. We estimate quantile regressions for every 5th quantile starting with the 10th and ending with the 90th. This amounts to 17 quantile regressions and 17 quantile regression coefficients for each of the explanatory variables.

The quantile regressions more or less confirm the results that we obtained from our matching estimations. Products new to the market are a highly significant determinant of high growth firms. However, the quantile regression approach also shows that products which are new to the firm are important
drivers for firm growth. Furthermore, we obtain a surprising result, namely that own innovations have a negative effect on high growth firms while they increase the growth rate of low growth firms. This result is robust to the replacement of the variable indicating own innovations with other innovation indicators (e.g. product innovations or process innovations). Our explanation of this result is that the own innovation variable captures the effect of uncertainty and risk with regard to innovation projects while TURNIN and TURNMAR primarily capture the effect of successful innovation projects.

Figure 5: Growth rate quantile regression results for manufacturing industries: organically growing firms

Thus, innovation is risky, yet successful innovation projects foster growth. At the same time, unsuccessful innovation projects slow down firm growth. This finding requires further analysis. We will follow Coad and Rao (2006) by using principal component analysis to summarize the information contained in the different innovation indicators into composite indices.

If we look at the country level (results not reported here), we find substantial differences across single countries, and again across the three EU-15 countries that are in the dataset (Spain, Germany and Belgium) and the two EU-10 countries (Czech Republic and Slovakia).

Unfortunately there are not enough observations in the micro-aggregated CIS 3 dataset to estimate “robust” quantile regression for the Innovation Watch - Systematic sectors. Hence, our analysis focused on the manufacturing industries only.

Since the results for the Austria micro data differ substantially due to the different gazelle definition we use in this case, we expect that the results from quantile regressions for other countries will be slightly different when we use employment-based Birch indices.
5. Summary and Discussion

In this paper we presented a number of preliminary results of the Innovation Watch – Systematic project about our research on the innovation behaviour of gazelles. Given the tremendous role in the process of structural change and employment generation, surprisingly little is known about the innovation of high growth firms. A short review of the literature presumes that gazelles are innovative by definition, since firms require a competitive advantage in order to achieve above average growth. This ‘competitive advantage’ can be achieved in a number of ways, such as through new products, innovative processes or technical change.

Given these very different types of innovativeness as drivers for growth, we expect to find gazelles in all sectors, and in fact we do. Estimating Laplace distributions, we also confirm that firm growth (and decline) is a rare event, since most firms do not change in size. As we are interested in the innovation behaviour of fast growing SMEs, we examine sample “outliers”, i.e. the top 10% of the distribution of sales growth rates. Thus, we refrain from applying standard econometric tools that are usually based on estimating variances from the mean. Instead, we use two different statistical methodologies: matching estimation and quantile regression.

We find that gazelles are indeed more innovative than other firms in terms of innovation success rooted in product diversification. Their share of turnover of products that are new to the market is significantly higher, and they also realise higher export growth. We obtain similar results with lower significance levels for the turnover share of products that are new to the firm only. They do not seem to be more R&D intensive when we use R&D per turnover. However, micro data for Austria indicates that R&D per employment is greater in gazelles than in other firms.

At the same time, we note that these results are based on micro-aggregated CIS 3 data, which may to some extent be distorted as a result of the process of anonymising the data. Using an employment growth based Birch index with Austrian micro data, we obtained similar, but slightly different results. This indicates that our results are sensitive to the choice of growth indicator, as each indicator to a certain degree selects other firms as gazelles.

References


Appendix:

B A closer inspection of the shape of the growth rate distribution

As a first step we tested whether the growth rate distributions are normally distributed. We the Shapiro-Francia test. We were able to reject the null of the normal distribution for all Systematic sectors. Table 7 presents the results.

Table 7: Shapiro-Francia normality tests
In a second step we go further and estimated the Exponential Power distribution (also known by the names of Subbotin distribution and generalized normal distribution) which nests the normal and the Laplace distributions as particular cases. We used Giulio Bottazzi’s software SUBBOTOOLS in order to do so.

Figure 6 displays the effect of a different parameter \( b \) on the shape of the distribution. If \( b \) equals 2 we obtain the normal distribution, if \( b \) equals 1 we obtain the Laplace distribution which has fatter tails than the normal distribution and last but not least if \( b \) equals 0.5 we obtain a distribution that has higher mass on the mean (in the case of the illustration 0) but fat tails.

\[ \]

**Figure 6: The effect of changes in the shape parameter \( b \) in the case of the exponential power distribution**

<table>
<thead>
<tr>
<th>Sector</th>
<th># firms</th>
<th>( W )</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Automobiles</td>
<td>359</td>
<td>0.771</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>Chemicals</td>
<td>665</td>
<td>0.809</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>Energy</td>
<td>287</td>
<td>0.791</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>Food</td>
<td>1033</td>
<td>0.599</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>Machinery</td>
<td>959</td>
<td>0.822</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>Textiles</td>
<td>1048</td>
<td>0.617</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>ICT</td>
<td>1076</td>
<td>0.757</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>ICT - man.</td>
<td>298</td>
<td>0.847</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>ICT - serv.</td>
<td>586</td>
<td>0.890</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>9257</td>
<td>0.733</td>
<td>0.050</td>
</tr>
<tr>
<td>Manufacturing EU 15</td>
<td>7158</td>
<td>0.702</td>
<td>0.005</td>
</tr>
<tr>
<td>Manufacturing Germany</td>
<td>1495</td>
<td>0.839</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>Manufacturing Spain</td>
<td>5085</td>
<td>0.705</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>Manufacturing Belgium</td>
<td>578</td>
<td>0.592</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>Manufacturing Czech Republic</td>
<td>1439</td>
<td>0.811</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td>Manufacturing Slovakia</td>
<td>660</td>
<td>0.802</td>
<td>&lt;0.0001</td>
</tr>
</tbody>
</table>

Note: \( H_0 \) is normal distribution
Table 7 reports the estimated parameters $b$ and $m$ of the exponential power distribution. The functional form of the exponential power distribution is characterized by three parameters, a location parameter $m$, a scale parameter $a$ and a shape parameter $b$, and reads

$$f(x; a, b, m) = \frac{1}{2ab^\frac{1}{b} \Gamma(1 + \frac{1}{b})} e^{\frac{|x-m|^b}{a}},$$

where $\Gamma$ is the gamma function. Bottazzi also derives a parameter estimation by maximum likelihood for an asymmetric exponential power distributions, where different values for parameters $a$ and $b$ are allowed for the two halves of the density.

The results in table 7 clearly show that the growth rate distributions for the Systematic Sectors are much closer to the Laplace distribution ($b=1$) than to the normal distribution ($b=2$). In fact the estimates suggest that the shape of the growth rate distribution is even more leptokurtic than the Laplace distribution, as all estimated shape parameter in the case of the symmetric exponential power distribution are less than 1. Also for the asymmetric distribution most estimated shape parameters are less than 1, with the exception of ICT manufacturing where we estimated a shape parameter of 1.026 for the left half of the density.

Table 7: Estimated parameters of the exponential power distribution for Systematic Sectors

<table>
<thead>
<tr>
<th>Sector</th>
<th># firms</th>
<th>Parameter estimates: symmetric distribution</th>
<th>Parameter estimates: asymmetric distribution</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>$b$</td>
<td>S.e.</td>
</tr>
<tr>
<td>Automobiles</td>
<td>359</td>
<td>0.730 (0.067)</td>
<td>0.189 (0.013)</td>
</tr>
<tr>
<td>Chemicals</td>
<td>665</td>
<td>0.747 (0.050)</td>
<td>0.174 (0.006)</td>
</tr>
<tr>
<td>Energy</td>
<td>287</td>
<td>0.690 (0.072)</td>
<td>0.075 (0.010)</td>
</tr>
<tr>
<td>Food</td>
<td>1033</td>
<td>0.610 (0.032)</td>
<td>0.122 (0.004)</td>
</tr>
<tr>
<td>Machinery</td>
<td>959</td>
<td>0.752 (0.042)</td>
<td>0.173 (0.006)</td>
</tr>
<tr>
<td>Textiles</td>
<td>1048</td>
<td>0.667 (0.035)</td>
<td>0.109 (0.006)</td>
</tr>
<tr>
<td>ICT</td>
<td>1076</td>
<td>0.694 (0.036)</td>
<td>0.259 (0.009)</td>
</tr>
<tr>
<td>ICT - man.</td>
<td>298</td>
<td>0.751 (0.076)</td>
<td>0.258 (0.015)</td>
</tr>
<tr>
<td>ICT - serv.</td>
<td>586</td>
<td>0.748 (0.054)</td>
<td>0.258 (0.013)</td>
</tr>
<tr>
<td>Manufacturing</td>
<td>9257</td>
<td>0.703 (0.012)</td>
<td>0.169 (0.002)</td>
</tr>
</tbody>
</table>

Note: $b$ is the shape parameter of the exponential power distribution. If $b=1$ the distribution is Laplace, if $b=2$ the distribution is normal. The estimated value of the scale parameter $a$ is not reported.