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A Quantile Regression Approach to Firm Growth

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Abstract:
This paper explores the firm growth rate distribution in a Gibrat's Law context. The aim is to provide an empirical exploration of the determinants of firm growth. The work is novel in two respects. First, rather than limiting the analysis to focus on the conditional mean growth level, we investigate the complete shape of the distribution. Second, we show that the differences in the firm growth rate process between large and small firms are highly circumstantial. That industry dynamics have a substantial influence on the relationship between firm size and firm growth. The data used includes more than 9000 Danish firms from manufacturing, services and construction. We provide robust evidence indicating that firm growth studies should be less obsessed with explaining means and instead look to other parts of the firm growth rate distribution.

Key words: Firm growth; quantile regression; distribution shape

Jel codes: C14; L11

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1 Introduction

It is very common to analyse firm growth and test Gibrat's Law using the OLS estimation method. This paper argues that this particular method is not the most appropriate in this respect. We argue that the quantile regression is a better approach, since it enables the researcher to consider the entire distribution of firm growth patterns, whereas OLS only considers the mean of the distribution. Recent evidence, reviewed below, have found that firm growth rate distributions tend to exhibit fat tails. This finding can basically not be picked up unless using quantile regression. In this paper, we study firm growth using quantile regression and find that there are considerable differences compared to results found when using the traditional OLS estimator.

Using data on more than 9,000 Danish firms, we look for specific industry characteristics that influence the dependencies of the firm growth process. Explaining firm growth using a quantile regression approach with estimates from every 5^{th} quantile, we investigate the full shape of the firm growth rate distribution and its dependency upon industry scale and firm specific effects. Interacting firm size with industry scale effects, we estimate the differences in firm growth rate distribution between large and small firms given the industry dynamics faced by the firm. Put differently this study tries not only to say something about the central moments of the firm growth rate distribution and its dependencies, but also uncover the devil that dwells in its tails.

Gibrat's Law (1931) represents the first formal model on the dynamics of firm size. Gibrat based his model on empirical data suggesting increments to firms size to be proportional to their current size. A number of studies have supported Gibrat's Law (see e.g. Hart and Prais (1956) and Simon and Bonini (1958)).

However, Gibrat's Law has also been questioned in numerous publications. First, Hymer and Pashigian (1962) and Mansfield (1962) found that the level of variance in growth rates is negatively correlated with firm size. Second, regression studies suggested firm growth to be negatively correlated with firm size (see e.g. Evans (1987a, 1987b), Hall (1987), Dunne, Roberts and Samuelson (1989), Dunne and Hughes (1994), Hart and Oulton (1996) and Reichstein and Dahl (2004)).[1]

Stanley et al. (1996) represents a different approach to investigate Gibrat's law by proposing that the shape of the empirical growth rate distribution is peaked and has fat tails resembling the exponential (Laplace) distribution rather than the Gaussian as otherwise assumed by Gibrat's Law. They proposed a revised Gibrat model in which the growth rate of firms depends not only on current size but also on previous size leading to an exponential-like growth rate distribution. Similar empirical patterns were found by Bottazzi et al. (2001, 2002) highlighting the tent-shaped pattern of growth rate distributions. Using a simulation approach, Bottazzi and Secchi (2003) were able to reproduce such patterns by revising an Ijiri and Simon (1977) type of model. Two mechanisms reproduce the empirical pattern. First, cumulative and self-reinforcing mechanisms in the way firms search for new solutions of opportunities as argued by Arthur (1994). Second, presence of firm specific capabilities discussed by among others Penrose (1959), Barney (1991, 2001), Foss (1997), Dosi et al. (2000), and Eisenhardt and Martin (2000). Finally, Reichstein and Jensen (2005) highlighted that the distributions were significantly

[1] However, this empirical finding has been attributed to sample attrition/selection bias. Exits are not included in the studies and are predominantly small firms producing a bias in the size variable in favour of small firms. Yet Harhoff, Stahl and Woywode (1998) indicated that the negative correlation persists even when controlling for sample attrition. For Gibrat's Law literature reviews, see e.g. Sutton (1997) and Lotti, Santarelli and Vivarelli (2003).

skewed with the right tails exhibiting more fatness than the left tails.

The latter of the above two approaches to firm growth argues that Gaussian statistics are unfit for studying firm growth. This is in co-junction with McKelvey and Andriani (2005). They argue that *managers live in the world of extremes; researchers using statistics report findings about averages* (McKelvey and Andriani 2005, pp. 224–225). Using Gaussian statistics like regression analysis is misleading and does not uncover details of particular importance. Instead of limiting our analysis to a central moment of a given distribution we should look at the full shape of the distribution.

This paper does that by using quantile regression to explain firm growth. To the best of our knowledge only one previous contribution is using quantile regression to study firm growth - namely the study by Lotti, Santarelli and Vivarelli (2003). Among other things, Lotti et al. found that small firms grow faster than large in specific industries and that this pattern is consistent across the 10^{th}, 25^{th}, 50^{th}, 75^{th} and 90^{th} quantile.

Despite numerous publication on Gibrat's Law and the relationship between firm growth and firm size, few studies have attempted to empirically explore how the correlation between the two is circumstantial. That industry specific circumstances dictates a difference in the growth process of small and large firms. Reichstein and Dahl (2004) argued that observed heterokedasticity from an OLS regression of firm growth against firm size to some extent may be explained by firm size having different effects on firm growth across industry borders. Studies on the shape of the firm growth rate distribution are carried out on the industry level arguing for differences across industries. However these fail statistically to explain how and to what extent the firm growth rate process differs across industry borders.

The outline of the paper is as follows. Section 2 describe the model used to study the firm growth rate distribution and how industry scale and firm specific effects shape different parts of the firm growth rate distribution. Section 3 shortly present the data and discusses the quantile regression approach. The results of the quantile regressions are reported in Section 4. Section 5 summarise the results.

2 The Model

Our analysis is based on the model developed by Davies and Geroski (1997). It investigates the determinants of changes in market shares. They draw heavily on the Gibrat's Law literature but augment the model by including both industry scale and firm specific effects. Additionally, the model includes a number of interaction effects between the size of the firm and the industry level variables. This provide the opportunity to distinguish between a common effect of firm size on firm performance and an effect which is circumstantial with reference to the dynamics of the industry.

The model tested in present paper may be represented by the following equation:

$$FGR_{ij} = \boldsymbol{\alpha_j} + \boldsymbol{\lambda_j} LFS_{ij} + \boldsymbol{\beta x_{ij}} + \mu_{ij} \tag{1}$$

where FGR_{ij} and LFS_{ij} are the growth rate and logarithm of size of firm i operating in industry j, respectively. μ_{ij} is the traditional independently identically distributed error term with zero mean and variance σ_{ij}. The terms in bold are vectors. $\boldsymbol{\alpha_j}$ and $\boldsymbol{\lambda_j}$ are vectors of industry scale variables, and $\boldsymbol{\beta}$ a vector of parameters estimates attached to a vector of firm specific variables, $\boldsymbol{x_{ij}}$. Specifically the vectors maybe represented by:

$$\boldsymbol{\alpha}_j = \alpha(RSG_j, HFD_j, MES_j, GRS_j, \boldsymbol{\psi}_j) \tag{2}$$

$$\boldsymbol{\lambda}_j = \lambda(RSG_j, HFD_j, MES_j, GRS_j) \tag{3}$$

$$\boldsymbol{x}_{ij} = (LFS_{ij}, LAE_{ij}) \tag{4}$$

The firm level vector, $\boldsymbol{x}_{ij}$, holds the logarithm of the firm size variable. However, it also contain a variable measuring the logarithm of firm age. This particular variable has been used through-out much of the firm growth literature (see e.g. Evans (1987a, 1987b), Dunne and Hughes (1994) and Jovanovich (1982)).

The industry scale vectors ($\boldsymbol{\alpha_j}$ and $\boldsymbol{\lambda_j}$) contain four common variables.[2] First, a measure of regional specialisation growth, RSG_j is included. This variable accounts for the growth of the firm attributable to the dynamics of the local region. Firms located in regions in which there is a high demand for final goods may exhibit a significant higher performance than firms outside such regions (Krugman 1991). Second, the Herfindahl index (HFD_j) is included to control for the concentration of the industry. Schumpeter (1942) argued that a high level of concentration would produce profits leading to a higher level of innovative activity and R&D expenditure. Third, we include a measure of minimum efficiency scale (MES_j) of the industry. This controls for the entry barriers in the industry, but also measures the extent to which incumbents can disregard an external com-

[2]For details on their measurement, see see Table 5 in the Appendix.

petitive pressure. Finally, a measure of the general growth of the industry (GRS_j) accounting for differences in growth trends across industry borders.

Contrary to Davies and Geroski, we do not interact all industry scale effect variables with firm size, so the two industry scale vectors (equation 2 & 3) are not identical. $\boldsymbol{\alpha}_j$ differs from $\boldsymbol{\lambda}_j$ by containing a vector, $\boldsymbol{\psi}_j$ with nine industries. Industry dummies control for potential variation in firm growth rates attributable to industry differences which the other industry variables cannot capture. It is not assumed that the effect of firm size differs significantly between these industry dummies. $\boldsymbol{\psi}_j$ is therefore not included in $\boldsymbol{\lambda}_j$.

3 Data and Method

The Data

The data used in the analysis is drawn from the NewBiz database published by Dansk Markeds Information A/S. The database contain all Danish limited liabilities, partnerships and limited partnerships and holds information on e.g. number of employees, industry classification, year of birth, geographical location and various financial variables. It contains information from 1993-1997 and is updated quarterly. Using 1993 and 1997 data is problematic as it leads to a substantial loss of observations, because the financial variables are imperfect in the first and last years. Consequently, we rely on 1994 and 1996 data for this analysis. Table 1 summarises the variables included in the model.

Figure 1 depicts the distribution of the dependent variable (FGR_{ij}). A Gaussian distribution with the mean and standard deviation values of the data is added as a reference. It reveals that the empirical distribution is considerable more peaked than the often assumed Gaussian shape. This also suggest the distribu-

Table 1: Descriptive statistics on non-interactive terms in the model (N=9105)

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
FGR_{ij}	0.052	0.525	-5.953	1.597
LFS_{ij}	8.904	1.978	1.386	16.077
LAE_{ij}	2.611	0.508	1.386	3.219
RSG_j	0.004	0.112	-0.565	0.936
HFD_j	0.028	0.062	0.000	1.000
ISB_j	0.105	0.072	0.000	0.501
MES_j	11.690	19.450	2.000	207.000
GRS_j	0.129	0.062	-0.597	0.349
Industry Dummies				
Supplier Dominated	0.087	0.281	0.000	1.000
Scale Intensive	0.074	0.262	0.000	1.000
Specialised Suppliers	0.040	0.195	0.000	1.000
Science Based	0.025	0.157	0.000	1.000
Construction	0.149	0.356	0.000	1.000
Wholesale Trade	0.149	0.356	0.000	1.000
Specialised Services	0.225	0.418	0.000	1.000
Scale Intensive Services	0.039	0.193	0.000	1.000
ICT Intensive Services	0.182	0.386	0.000	1.000

tion to have fatter/heavier tails giving support to the recent studies on the shape of the firm growth rate distribution (see e.g. (Stanley, Amaral, Buldyrev, Havlin, Leschhorn, Maass, Salinger and Stanley 1996, Bottazzi, Dosi, Lippi, Pammolli and Riccaboni 2001, Bottazzi, Cefis and Dosi 2002, Reichstein and Jensen 2005)). It also suggests that alternative methods should be considered rather than relying on the traditional OLS regression method.

Method

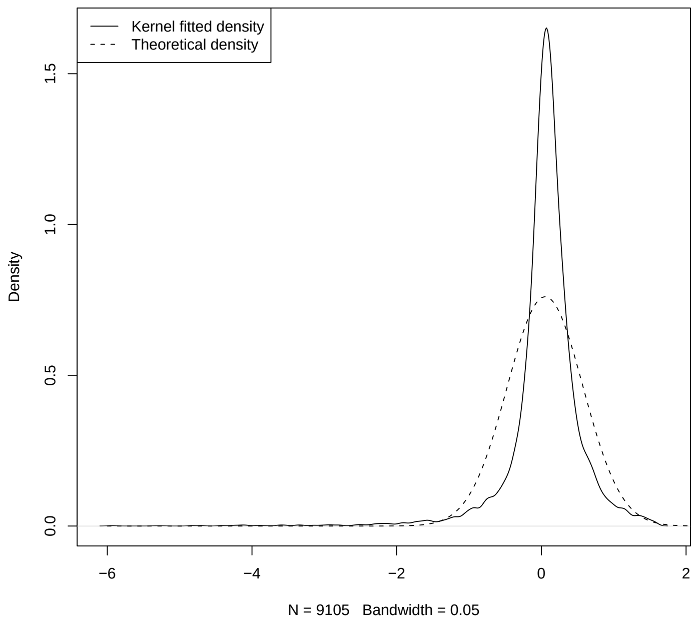


Figure 1: Empirical Firm Growth Rate Distribution and Associated Gaussian Distribution

The shape of the firm growth rate distribution calls for a different approach than the traditional OLS regression method. The OLS assumes the dependent variable to be Gaussian distributed. Quantile regression represent an alternative tool of analysis which do not assume any particular form of the distribution of the dependent variable. Compared to OLS regression, quantile regression provide a more complete story of the relationship between variables, because it does not limit itself to regressing against averages and hence explain averages (Koenker 2005). We apply the linear quantile regression method introduced by Koenker and Bassett (1978) to investigate the factors influencing firm growth rates. This approach has two major advantages. First, it reveals differences in the relationship between the endogenous and the exogenous variables at different points of the conditional distribution of the dependent variable. Rather than focusing on a specific moment of the distribution, linear quantile regression represent a method of analysis suitable for studying all defined values of the dependent variable. It hence enables us to say something about the dependencies of the tails as well as the central values of a distribution of a given dependent variable.

Second, the coefficient estimates of the quantile regression are more robust than those of 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 (see Buchinsky (1998), Koenker and Hallock (2001)). This is not least important when studying a dependent variable which is not Gaussian.

Koenker and Basset (1978) suggest to either study how one specific quantile of particular interest in linearly correlated with a set of explanatory variables or study how the linear correlation changes across a number of quantiles. The latter of these approaches will provide an understanding of the entire shape of the distribution and how it may be shaped by the explanatory variables.

Consider the linear regression model $y_i = \boldsymbol{x_i}\boldsymbol{\beta} + u_i$ for $i = 1, \ldots, n$ where $\boldsymbol{x_i}$ and $\boldsymbol{\beta}$ are k vectors of explanatory variables and their estimated coefficients respectively. y_i and u_i are the dependent variable and the iid distributed error term, respectively. The OLS estimator is found by minimising the sum of the squared residuals:

$$\min_{\boldsymbol{\mu} \in R^k} \sum_{i=1}^{n} (y_i - \mu)^2 \tag{5}$$

The quantile regression estimator on the other hand is the vector $\boldsymbol{\beta}$ that minimises:

$$\min_{\boldsymbol{\beta} \in R^k} \left[\sum_{i \in \{i: y_i \geq \boldsymbol{x_i \beta}\}} \tau \left| y_i - \boldsymbol{x_i \beta} \right| + \sum_{i \in \{i: y_i < \boldsymbol{x_i \beta}\}} (1-\tau) \left| y_i - \boldsymbol{x_i \beta} \right| \right] \tag{6}$$

τ is the quantile defined as $Q_{Y|X}(\tau|x) = \inf\{y : F_{X|Y}(y|x) \geq \tau\}$ in which τ is bounded between zero and one, and y is a random sample from a random variable, Y, which have the distribution function F ($F(y) = P(Y \leq y)$).

Equation 6 is the objective function and represents an asymmetric linear loss function. For $\tau = 0.5$, however, it becomes the absolute loss function determining the median regression. One of the strengths of the quantile approach is that τ may vary within its bounded interval ($0 < \tau < 1$) representing different quantiles. Doing so reveals the conditional distribution of y given $\boldsymbol{x}$. The coefficient estimate for the exogenous variable is interpreted in much similar fashion as OLS regression coefficients. The quantile coefficients may be interpreted as the marginal change in the dependent variable due to a marginal change in the exogenous variable conditional on being on the τ-th quantile of the distribution. Changing estimated coefficients with varying quantiles is indicative of heteroskedasticity issues (Koenker 2005).

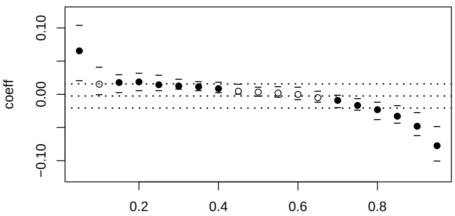
4 Results

In this section, we empirically investigate how the firm growth rate distribution is shaped by firm characteristics and industry circumstances. In particular, we explore to what extent the effect of firm size is dictated by the dynamics of the industry. The results of the quantile regressions are represented by the figures 2(a) through 3(f). The horizontal axis of the diagrams represent the quantiles. The vertical axis represent the estimated coefficients. We estimate quantile regressions for every 5^{th} quantile starting with the 5^{th} and ending with the 95^{th}. This amounts to 19 quantile regressions and 19 quantile regression coefficients for each of the explanatory variables. These are represented by the circles. A black circle represent the significant estimates while an empty represent an insignificant coefficient.

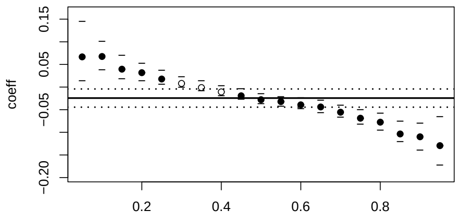
We have also estimated the corresponding OLS regression represented by the horizontal lines. Three lines are included. The middle line represents the estimated coefficient while the two lines on each side represent the confidence interval at a 10% level. A dash-dotted line represent a significant estimate while a dotted line represent an insignificant OLS coefficient. The significant OLS coefficients are therefore those associated to the logarithm of firm age (LAE), the industry concentration level (HFD), and the interaction term between logarithm of firm size and the industry concentration level.[3]

Including both quantile and OLS regression results reveal a substantial difference between the results of the two types of regressions. While the results of the OLS regression suggest firm size not to be significant in explaining firm growth, the quantile regression results suggest firm size to be significant in explaining both the lower and the upper quantiles of the firm growth rate distribution. A similar pattern is observed for the age of the company. The OLS estimate is significant. But this significance is even more expressed in the tails of the distribution

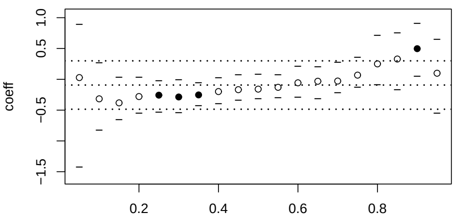
[3]The standard errors of the OLS regression estimates have been corrected for bias in terms of heteroskedasticity. We have followed Long and Erwins (2000) recommendations using the MacKinnon and White (1985) method.



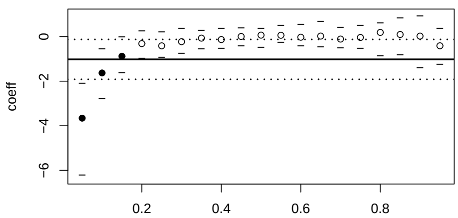
(a) Logarithm of Firm Size (LFS)



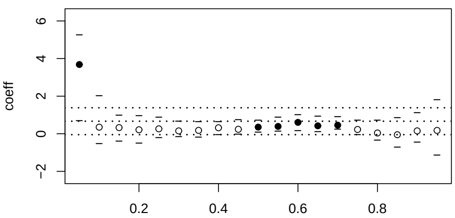
(b) Logarithm of Firm Age (LAE)



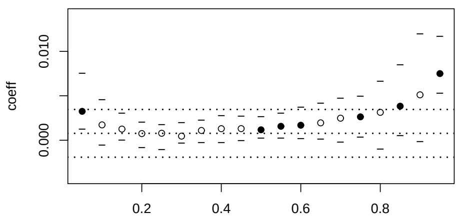
(c) Regional Specialisation Gr. (RSG)



(d) Industry Concentration (HFD)



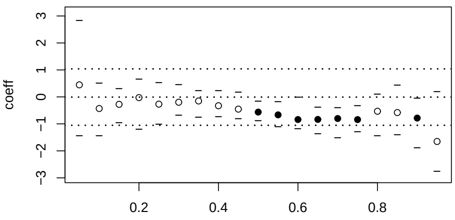
(e) Industry Instability (ISB)



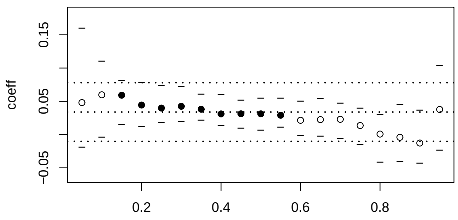
(f) Minimum Efficiency Scale (MES)

Figure 2: Quantile regressions

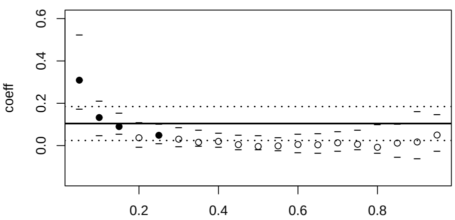
suggested by the quantile regression results. The pattern of quantile regression coefficients considering firm size and firm age, suggest the tails to be fatter for young and small firms.



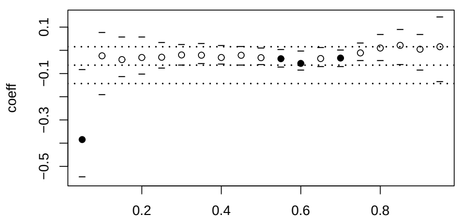
(a) Industry Growth (GRS)



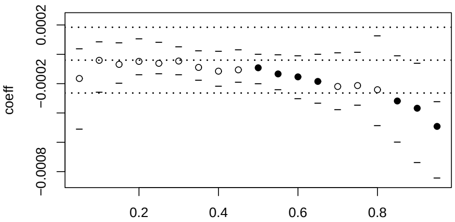
(b) $LFS * RSG$



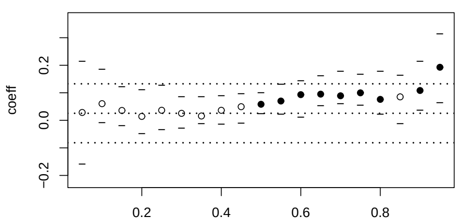
(c) $LFS * HFD$



(d) $LFS * ISB$



(e) $LFS * MES$



(f) $LFS * GRS$

Figure 3: Quantile regressions (continued)

The industry variables also exhibit some interesting differences between the OLS and quantile regression results. The OLS results suggest the concentration level alone to be significant. The quantile regressions depict a much richer pattern.

With regard to the concentration level the quantile regressions indicate concentration to be negatively significant when regressing against the lower quantile. This suggest that industries with a high level of concentration have a tendency to be located in the lower end of the growth rate distribution. It is for this reason that the OLS estimate becomes significantly negative. Firms operating in industries characterised by high minimum efficiency scale circumstances enjoy both advantages and disadvantages. There is a difference in the skewness of the firm growth rate distribution between firms operating in high and low efficiency scale industries.

The industry growth variable tends to be significant when regressing against the upper quantiles and insignificant when regressing against the lower quantiles. The significant estimates are negative suggesting that firms operating in low growth industries, however may be experiencing extreme high growth rates.

Studying the results in terms of the interaction effects it is clear that the effect of firm size on firm growth partly is dictated by industry circumstances. Interacting the logarithm of firm size with the regional specialisation growth variable and the industry growth variable exhibit significant estimates in the lower and upper quantiles respectively. This suggests that there are tail effects of industry dynamics on the firm size firm growth relationship.

The significant estimates in figure 3(b) are limited to the 55^{th} and lower quantiles except the 5^{th} and are positive. This sugests that the firm growth rate distribution tend to have a less fat lower tail if the large firm is located in a region which increases its specialisation in the particular industry in which the firm is operating. Large firms benefit to a greater extent to increases in specialisation in a regionally bounded area.

Finally the quantile regressions suggest firm size to have a positive impact on firm growth rates when the firm is located in industries experiencing high growth rates. This is particular true when regressing against the upper quantiles. All quantiles above the 45^{th} except the 90^{th} exhibit significant positive estimates in figure 3(f) indicating large firms operating in high growth industries tend to exhibit firm growth rate distribution with fatter upper tails. They are hence more likely to exhibit extreme growth rates than they counterparts.

5 Concluding Remarks

The purpose of this paper is to study factors influencing the growth of firms. In particular, we apply an alternative regression method enabling a deeper study of this phenomenon by considering the entire distribution of firm growth and not only the mean.

We find considerable differences between the results of the OLS regression compared to the quantile regressions. Firm size is insignificant in the OLS regression, but the quantile regression reveals that firm size has a significant impact on firm growth on a considerable part of the distribution. Similar results are found for the interactions between firm size and growth in regional specialisation as well as between firm size and industry growth. In the other direction, the OLS regression show significant impacts of industry concentration and the interaction of industry concentration and firm size. These finding are largely rejected in the quantile regression, which find that this is only the case for a few quantiles at the left end of the distributions. We suspect that the findings on OLS regression is driven by a few extreme outliers, which clearly influences the mean. These finding show that the results can literally turn around, if a more careful method is applied.

For future research, we recommend that studies of firm performance should consider applying the quantile regression approach as it will reveal greater details on the patterns, which are otherwise overlooked in conventional OLS analysis.

Appendix

Table 2: Variable Descriptions

Abbreviation	**Description**
FGR_{ij}	Firm sales growth 1994-1996. It is calculated by using logarithmic transformation ($\log(FS_{ijt}) - \log(FS_{ijt-1})$)
LFS_{ij}	Logarithm of firm size. Size is measured by firm sales in 1994 ($\log(FS_{ij})$) in thousands of Danish Kroner.
LAE_{ij}	Logarithm of age of the firm. Measured by the 1994 less the year of establishment.
RSG_j	Regional specialisation growth. Regional specialisation is calculated using the revealed comparative advantage index (RCA_j) (Balassa 1965). RSG_j is then calculated by the growth of the RCA_j from 1994 to 1996.
HFD_j	The Herfindahl concentration index calculated by the sum of the squared share of sales across the industry. ($\sum_{i=1}^{n} \left[\frac{FS_{ij}}{\sum_{i=1}^{n} FS_{ij}}\right]^2$).
ISB_j	The instability index is measured using the Hymer and Pashigian approach summing the absolute changes in market shares by three digit industry codes ($\sum_{i=1}^{n} \left\| \frac{FS_{ijt}}{\sum_{i=1}^{n} FS_{ijt}} - \frac{FS_{ijt-1}}{\sum_{i=1}^{n} FS_{ijt-1}} \right\|$).
MES_j	Industry minimum efficient scale of production measured by medium size of the firms in the industry using employment statistics.
GRS_j	Growth of the industry measured by the difference in logarithms of industry sales from 1994 to 1996 using a three digit level of aggregation.

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