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Financial Fragility and the Distribution of Firm Growth Rates

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Financial fragility and the distribution of firm growth rates*

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Abstract

Analyzing a comprehensive database of limited liability manufacturing firms this paper investigates the relation between a firm's financial situation and its conditional expected growth rate. Specifically, using quantile regressions, we obtain a quantitative characterization of this relation for different quantiles of the growth rates distribution. We find that simple location-shift models, as for instance the OLS, provide a poor and potentially misleading representation of the growth-finance relation. Indeed, the vast majority of the explanatory variables considered are associated with modifications in the support of the growth rates distribution (scale-effect), even when the relation of the same variables with the expected growth is negligible. Moreover, we show that financial conditions impact differently on the growth dynamics of young and old firms. Finally, our investigations reveal that the results obtained with quantile regressions appear robust with respect to possible mispecifications of the empirical model.

JEL codes: L11, C14, D20, G30

Keywords: Firm growth, Quantile regression, Financial constraints, Firm size distribution, Credit risk ratings

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1 Introduction

From capital investment (Fazzari and Petersen, 1993; Bond et al., 2003) to R&D spending (Hall, 2002; Brown et al., 2009) many aspects of firm operations are affected by the availability of financial resources. Thus, the growth pattern of business companies is likely to depend on their ability to find affordable money to expand, or maintain, their current business. The relation between financial constraints (FC) and the growth dynamics of firms, has been addressed in a series of recent works. While the theoretical literature is essentially unanimous in pointing at the hampering effect that FCs should exert on firm growth (see for instance Cooley and Quadrini, 2001; Clementi and Hopenhayn, 2006), empirical results are contrasted. On the one hand, Cabral and Mata (2003), measuring the availability of financial funds with age, find that the evolution of the firm size distribution is determined by firms ceasing to be financially constrained. The multi-variate analysis proposed in Becchetti and Trovato (2002), and performed over a sample of small manufacturing firms, confirms the negative effects of credit rationing on growth. On the other hand, Fagiolo and Luzzi (2006), studying the reported cash flow of a large panel of firms, conclude that the lack of FC is not among the main determinants of firms growth. Similar conclusions are drawn by Angelini and Generale (2008), who analyze instead a survey-based measure of access to credit.

A common difficulty that this literature faces is the identification of a reliable proxy of financial constraints. Different measures have been proposed: relative rankings in the cross-sectional distribution of variables likely correlated with the availability of funds (Fazzari et al., 1988; Kaplan and Zingales, 2000), multivariate indexes based on a number of financial ratios (Whited and Wu, 2006; Musso and Schiavo, 2008), or answers to specific questions in business surveys (Winker, 1999; Campello et al., 2010). None of these approaches is without its pitfalls and they tend to produce quite different classifications.[1] However, another factor which can possibly explain the inability to persistently identify the economic effects associated with financial constraints is the econometric framework adopted to investigate and measure them. Traditional analysis are indeed based on ordinary regression models. These models are exclusively designed to capture a location-shift effect, possibly induced by FCs, in the conditional distribution of the dependent variable. The only question which can possibly be addressed by these models is whether the presence of financial constraints is associated with a modification, on average, of the performance measure under scrutiny (productive investment, R&D expenditure, share of export and so on).

The idea that a simple location-shift framework is sufficient to capture the effects of FC seems, however, too simplistic and not in line with the most recent empirical evidence. Indeed, in a recent paper based on survey data, Campello et al. (2010) report that firms display significant heterogeneity in their responses to financing problems: some firms react by abandoning investment projects, despite their perceived potential, while other firms, especially those which are already experiencing poor growth, have a much higher propensity to sell off productive assets as a way to generate funds. Analogously, Bottazzi et al. (2008) find that the accessibility and cost of external finance characterizes firms which are extremely different both in terms of financial structure and operating performances. The multiplicity of channels through which FCs affect the business activity of firms and the multitude of economic aspects on which they impact require, in fact, more flexible econometric models, able to capture the different effects which are likely to be observed for different firms. At the same time, it seems mandatory

[1] In order to justify their measure based on cash sensitivity to cash flow, Almeida et al. (2004) perform a comparison of various FC definitions. It turns out that the similarity between the sets of financially constrained firms obtained using different definitions is in fact rather low.

not to rely on a single measure of credit rationing but consider instead multi-variate models including variables accounting for different sources of financial fragility.

Motivated by the considerations above, in this contribution we propose to extend the traditional regression analysis of the relation between FCs and firms growth adopting a quantile regression (QR) framework. The methodology of quantile regression has recently gained momentum because of its flexibility and robustness (Koenker and Hallock, 2001). To our knowledge, however, it has never been applied in this literature before. As we will see, this technique is effective in widening our perception of the effects induced by FCs. We will show that QR are indeed able to reveal strong and persistent association between the growth patterns of firms and several financial variables even when their average, location-shift, effects would have been negligible. Many variables do indeed play a role through their scale effect, that is the variability of economic performances they induce in the cross-sectional distribution of firm growth rates. Other variables, conversely, display more complicated patterns, inducing a reduction, or expansion, of economic performances only for firms with extreme growth behaviors.

Moreover, instead of relying on a single index to measure firm's availability of financial resources, we consider a series of financial variables, ranging from collateral to leverage, which are likely to capture both the internal and external availability of funds. These proxies are complemented by a risk rating index, which provides a concise assessment of a firm's solvency and accounts for a wide range of potential sources of financial problems.

Finally, in addition to the general assessment of the distributional impact of the different financial variables, we intend to apply quantile regressions to investigate to what extent the relation between financial fragility and growth is mediated by firm age. Bottazzi et al. (2012), using a distributional analysis based on the residuals of a robust Least Absolute Deviation (LAD) estimation, show that the effect of financial constraints differ between firms which are young and small and those which are older and bigger. The QR analysis preformed in the following confirms these findings and reveals that the variation of some explanatory variables, most notably leverage, has opposite effects on the two groups of firms. The asymmetry in the effect that the temporary reduction of financial resources has on firms of different ages and sizes bears relevant policy implications, given the roles that newborn firms have both in terms of productivity improvement (Bartelsman et al., 2004) and job creation (Davis et al., 1996; Haltiwanger et al., 1999, 2010).

In the next section we introduce the data and the relevant variables. In Section 3, using the simplest specification, we present a very short introduction of the quantile regression framework, explaining the meaning of the plots reporting estimates and what can be understood through their inspection. Section 4 discusses the main specification of the model and its results. A few extra specifications, devised to address potential issues contained in the main model, are discussed in Section 5. Finally, Section 6 summarizes our results and concludes.

2 Data

Our analysis is based on an unbalanced panel of $161,297$ Italian firms active in manufacturing over the period 2000-2003.[2] The source of data is a large database of Italian firms maintained by the Italian Company Account Data Service (CeBi-CERVED). This database is of a business register type, collecting annual reports for virtually all limited liability firms. Our unbalanced

[2]Our sample contains an average numbers of firms per year of about $114,000$ with more than $82,000$ firms present in all the four years.

Table 1: DESCRIPTIVE STATISTICS FOR YEAR 2003

	Median	Interdecile range	Interquartile range	Min	Max
Total Sales	6,911.328	32,857.240	11,195.090	0.966	15,119,600.000
Age	19.000	35.000	16.000	0.000	185.000
Tangible assets	1,194.295	7,620.285	2,758.280	0.928	2,190,785.000
Gross operating margins	490.179	3,115.690	1065.009	1.000	392173.900
Leverage	0.297	0.520	0.285	0.000	278.835
Risk Rating	5.000	5.000	2.000	1.000	9.000

Notes: Nominal figures are in thousands of euro and deflated with a 3-digit sectoral producer price index (base year 2000).

panel accounts for about 45% of total employment and about 65% of aggregate value added of Italian manufacturing sector, over the years of observation. Annual reports are filtered by excluding firms reporting only one employee. These are legal entities where the proprietor and the employee coincide. Typically these firms represent two different economic phenomena: self-employment and group holdings. Both are peculiar phenomena and they are plausibly characterized by dynamics which are somehow different from those of the typical business firm. In order to obtain a more homogeneous population we decided to ignore them.[3]

Our analysis relates financial and operating aspect of firm dynamics, so we need to consider different variables able to capture both dimensions. On the financial side, we choose two sets of proxies to measure both the internal and the external sources of financial resources. For the former, we take a measure of operating cash flow, the gross operating margin, defined as revenues minus costs but before interest, taxes, depreciation, and amortization (often called EBITDA). For the latter, we consider a measure of collateral availability and a measure of the overall financial fragility of the firm. The first is proxied by tangible assets, including both physical capital (machinery, buildings and land) and inventory, the second by a leverage index defined as the ratio between financial debts and total assets. Notice that in our definition of leverage we take financial debts, instead of total debts, in order to sterilize the potential biasing role of commercial debts. In addition, we consider a firm Risk Rating index directly provided by CeBi-CERVED and intended to yield a concise assessment of a firm's solvency. This index results from a multivariate score analysis, accounting for a wide range of potential sources of financial problems and incorporating the "opinion [of credit suppliers] on the future obligor's capacity to meet its financial obligations" (Crouhy et al., 2001, p.51). It thus reflects financial markets' evaluation of the credit quality of the firm (Whited, 1992; Almeida et al., 2004). The rating index is a score ranking firms in 9 categories of creditworthiness: 1-high reliability, 2-reliability, 3-ample solvency, 4-solvency, 5-vulnerability, 6-high vulnerability, 7-risk, 8-high risk, and 9-extremely high risk.

As a measure of firm size we take total sales, that is net annual revenues plus inventory variation. This is a measure of the overall production capacity and of the commercial success of a firm.[4] Moreover we consider age, computed from the year of foundation, and a 3-digit

[3] Our choice is also justified by the observation that single and multi employees firms display extremely different statistical properties (see "Data description and sample selection" in Bottazzi et al. (2008))

[4] Another traditional measure of firm's productive capacity is the number of employees. Due to the Italian accounting rules, however, employment figures are not directly reported in financial statement, and are therefore less reliable. For small firms especially, a mistake of even few units of personnel in employment reports

sectoral dummy, assigned to each firm according to the classification of its main activity, as further controls.

All monetary variables, that is total sales, tangible assets and gross operating margins, are deflated using 3-digit sectoral production price index with base year 2000 made available by the Italian Statistical Office. Table 1 reports descriptive statistics for the financial and operating variables in 2003.

3 Univariate analysis

Let $y_{i,t}$ be the (log) total sales of company i in year t and define the corresponding growth rate as $g_{i,t} = y_{i,t} - y_{i,t-1}$. Further, let $X_{i,t}$ be an array of firm-specific, explanatory variables defined over the entire sample. The traditional linear regression model aims to estimate the relation

$$E[g_{i,t}|X_{i,t-1}] = \alpha + \beta X_{i,t-1} \ , \tag{1}$$

where E is the conditional expectation operator of the dependent variable, in this case the growth rate, given the value taken by the covariates in X. In the simplest case, when α and β are independent from t and i, this linear relation can be estimated. for instance, via Ordinary Least Squares (OLS). Under specific assumptions about the conditional distribution of g, this is equivalent to a maximum likelihood estimation. In more general situations, for instance when the coefficient α and β are assumed to be firm specific (panel data), when lagged realizations of the dependent variable are included among the independent variables (autoregressive or moving average specifications) or when some degree of heteroskedasticity is presumed, more sophisticated multi-stage methods become mandatory to obtain consistent and unbiased estimates. In any case, whatever the method adopted, the obtained point estimates $\hat{\alpha}$ and $\hat{\beta}$ do retain the same meaning: an increase of δX in the independent variables generate an increase of $\hat{\beta}\delta X$ in the conditional expectation of g. In this sense, the only relation between the variables X and the variable g that this framework is able to capture is a modification of the mean of the conditional distribution of the latter. This is often referred to as a "location-shift" effect.

Conversely, the linear quantile regression model is aimed to estimate the relation

$$Q_\theta[g_{i,t}|X_{i,t-1}] = \alpha_\theta + \beta_\theta X_{i,t-1} \ , \tag{2}$$

where Q_θ is the conditional quantile function, that is the value of the θ-th quantile of the distribution of g, conditional on the values taken by the independent variables X. A pair of estimates $(\hat{\alpha}_\theta, \hat{\beta}_\theta)$ can be obtained for each value of $\theta \in [0, 1]$. If these estimates do not depend on the value of θ, we are back to the ordinary case: a change of δX in the independent variables is associated with a variation equal to $\hat{\beta}\delta X$ in all the quantiles, which generates a uniform shift in the conditional distribution of g. In general, however, the shift induced in the dependent variables varies with θ, that is with the quantile considered, so that firms whose growth rate belongs to different quantiles will be differently affected by the same variation of the independent variables.[5]

To introduce our empirical investigation and to illustrate how to read the curves which are the QR equivalent of point estimates, let us present a simple QR model with one single

may produce a huge error in the measurement of employment growth rates

[5] For an introduction to quantile regression see Koenker (2005). The asymptotic properties of the QR estimator are discussed in Koenker and Basset (1978).

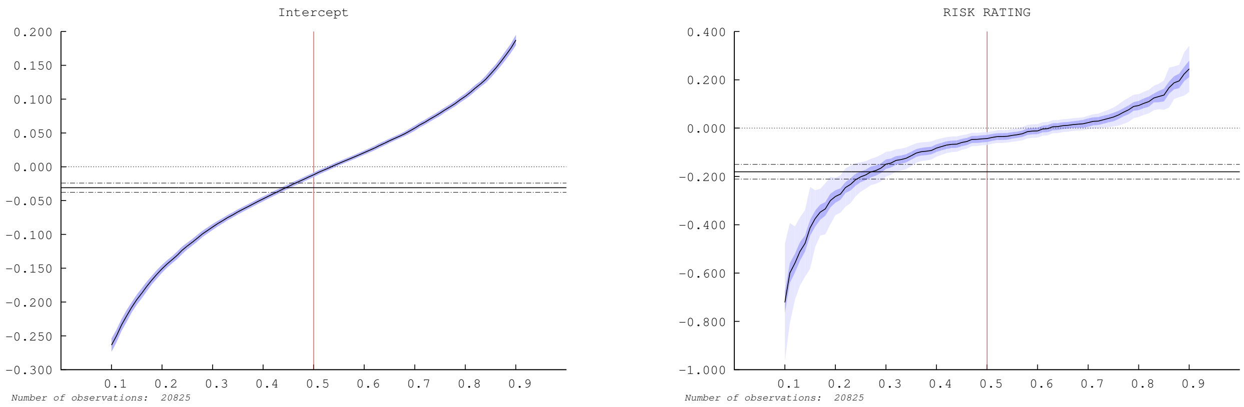

Figure 1: Quantile regression estimates of Equation 3 for 2003. Shadow bands represent 99% confidence intervals obtained using kernel approximation to the local density (light shadow) and the asymptotic covariance matrix assuming i.i.d. errors (dark shadow). OLS estimates are also reported (solid horizontal black line) with a corresponding 99% confidence band.

regressor

$$Q_\theta[g_{i,t}|RR_{i,t-1}] = \alpha_\theta + \beta_\theta RR_{i,t-1} \ , \tag{3}$$

where RR (for "risk rating") is a dummy variable taking value 1 if the CeBi-CERVED risk rating is strictly bigger than 7 and zero otherwise. The RR dummy identifies those firms which are in fact more likely to be considered problematic by their institutional lenders.[6] The present analysis is restricted to year 2003, so that the sample contains $20,825$ observations. The point estimates of α and β for the different quantiles are reported in Figure 1. The shaded areas correspond to 99% confidence intervals. There are two kinds of shade: the lighter one is obtained using kernel approximation to the local density while the darker is based on the asymptotic covariance matrix assuming i.i.d. errors.[7] For comparison, we also report the estimates and confidence intervals obtained with an OLS regression.

The left hand plot reports the estimate of α_θ. This is the quantile function, that is the inverse distribution function of the growth rate of low-risk firms (ie those with RR equal to 0). These firms have, in 2003, an average growth rate of around -0.05. However, the median growth rate of these low-risk firms is around zero and approximately 45% of them see their business increase with respect to the previous year. The top quartile, that is the 25% of the firms that grow the most, have growth rates greater than 10%.

The picture on the right hand side shows the effect induced on the distribution of firm growth rates by being risky. The average effect is a reduction of almost 0.2 in the expected growth rates (OLS estimates). That is, on average, risky firms have a growth rates of about -0.25. In fact a careful observation of the plot suggests that the induced patterns are more complex. First, the growth rate of the modal firm is barely affected by its risky status: the point estimates of $\beta_{0.5}$ is indeed only slightly below zero. Second, looking at the top 30% of the growth rates distribution of risky firms, we observe an increase, and not a reduction,

[6]The source of information in this case is mainly private communication with people working inside commercial banks. As we will see in Section 5, however, changing the definition of the dummy does not change our conclusions.

[7]For the discussion of the different estimators of the confidence interval see Koenker and Hallock (2000) and reference therein. Both point estimates and confidence intervals reported in the present paper are obtained using the package `quantreg` for the `R` statistical software as described in Koenker (2012)

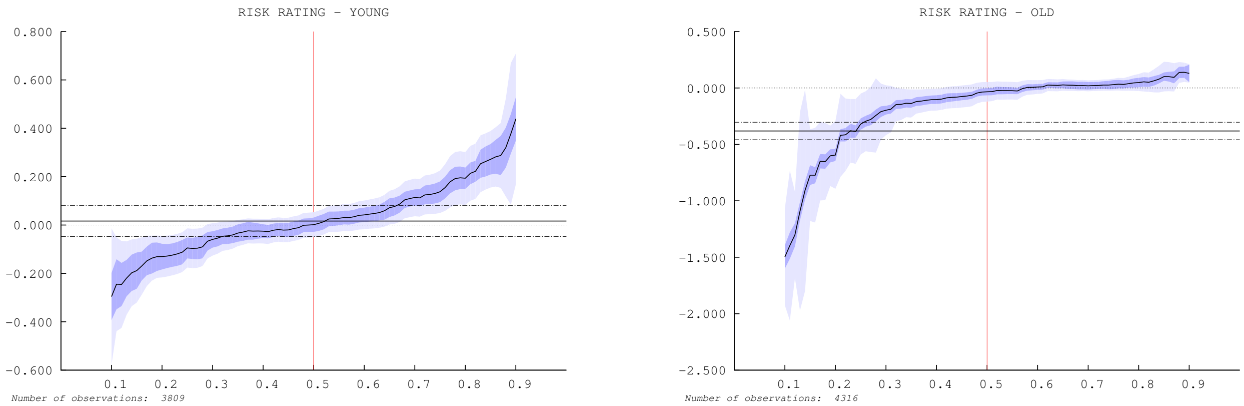

Figure 2: Quantile regression estimates of the risk rating dummy RR in Equation 3 for 2003. Shadow bands represent 99% confidence intervals obtained using kernel approximation to the local density (light shadow) and the asymptotic covariance matrix assuming i.i.d. errors (dark shadow). OLS estimates are also reported (solid horizontal black line) with a corresponding 99% confidence band. Young firms in the left panel, old firms in the right panel.

of their annual growth rate with respect to the distribution of non risky firms. In summary, the most prominent effect implied by having a risky status is a widening of the support of the distribution of growth rates. The population of riskier firms is characterized by more heterogeneous performances than the population of non risky firms, while the typical, median, behavior is not so much different between the two groups.

Further insights on the relation between growth patterns and the variable RR can be obtained by investigating separately two sub-samples: one including young firms (less than 10 years) and the other including old firms (more than 30 years). As discussed in the introduction, the effect on these two samples is expected to be different. Notice that, apart form their age, these two samples are likely to differ also in many other respects. In particular, all the variables which are related with size, like turnover, number of employees, assets, equity or debts are surely higher in the second sample. At this preliminary stage of the analysis, it is however instructive to see how the growth rate and the risk rating correlate in the two groups of firms. The results of these regressions are reported in Figure 2.

In the case of young firms, a standard regression would not support the existence of a relation between RR and the expected growth rate: the OLS estimates is not statistically different from 0 (cfr. left panel of Figure 2). The QR estimates reveal, on the contrary, a rich and interesting picture. Indeed, a big deal of firms, in practice those having growth rates in the quantile range from 0.3 to 0.7 (ie around 40% of the entire sample), are basically unaffected by the risk rating. On the other hand, in the extremal deciles of the distribution, the correlation between growth and RR becomes huge: in the second decile is a remarkable -0.3 while in the ninth decile is 0.2. This confirms also for young firms the symmetric widening effect observed in the aggregate.

The situation that emerges for older firms is different. In this case the correlation in the higher quantiles is very mild, barely above zero. On the contrary, in the lower decile the risky status is associated with a reduction in growth rates of -1.5, which means an additional loss of around 80% of revenues with respect to the previous year. The extremal behaviour of these bad performing firms is responsible for the huge reduction in average growth rates (OLS estimate), which is around -0.4. On the other hand, the effect on the median firm is

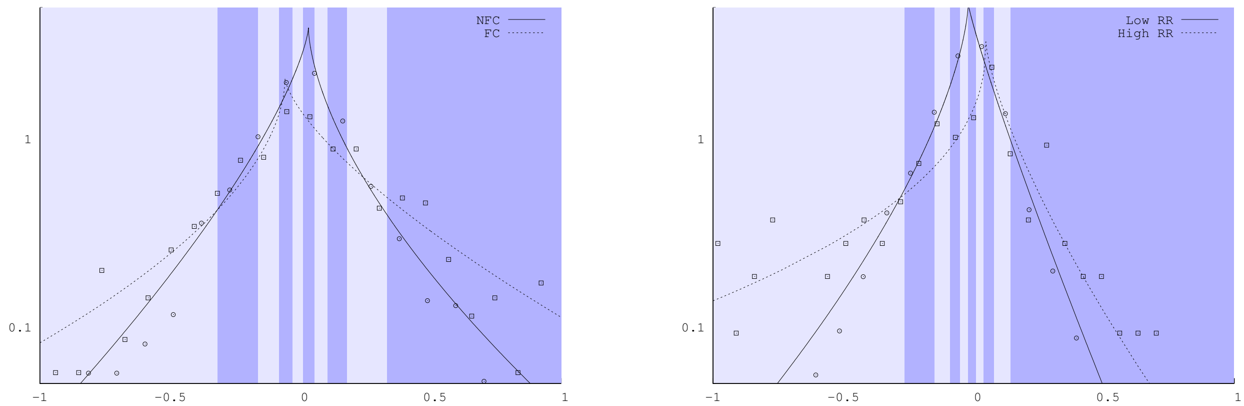

Figure 3: Histograms of the empirical densities of growth rates for risky ($RR = 1$) and non-risky ($RR = 0$) firms for 2003. Maximum likelihood estimates of an Asymmetric Power Exponential distribution are also reported. Shadow-areas represent the 10 deciles of the distribution. Young firms in the left panel, old firms in the right panel.

not significantly different from zero.

In the case of a simple univariate analysis as in (3), the amount of information which can be obtained running a QR regression is roughly equivalent to the information available through visual inspection of the conditional density functions. In Figure 3, histograms of the empirical densities of growth rates are reported for the two populations of risky and riskless firms. To help the reader's eye, we superimpose the estimate of an Asymmetric Power Exponential distribution, which better captures the asymptotic behaviour in the tails (Bottazzi and Secchi, 2011). The plots confirm the scale-shift effect of the RR dummy and its role in the tails of the distribution.[8]

In conclusion, the distribution of growth rates of risky and non risky firms is significantly different. This is true both in the aggregate and if one considers young and old firms separately. This result suggests that the limited access to external finance which is plausibly implied by a bad score of the CeBi-CERVED credit risk rating plays a relevant role in shaping the operating performances of firms. As we will see in the next section, this result remains unchanged when multi-variate models are considered.

4 Multivariate analysis

In this section we consider a multivariate linear quantile regression with the growth rate $g_{i,t}$ as the dependent variable. Specifically we estimate the autoregressive model

$$Q_\theta[g_{i,t}|X_{i,t-1}] = \alpha_\theta + \beta_\theta X_{i,t-1} + \sum_{l=1}^{L} \gamma_l g_{i,t-l} \ , \tag{4}$$

with the lagged dependent variable among the explanatory variables. The estimate is performed on the cross-section data available in year 2003 which allows us to set $L = 2$. The vector of lagged independent variables $X_{i,t-1}$ contains: Size, defined as the logarithm of annual

[8]Visual inspection of the conditional densities is of course not an option when multivariate models are considered, as we do in the next section.

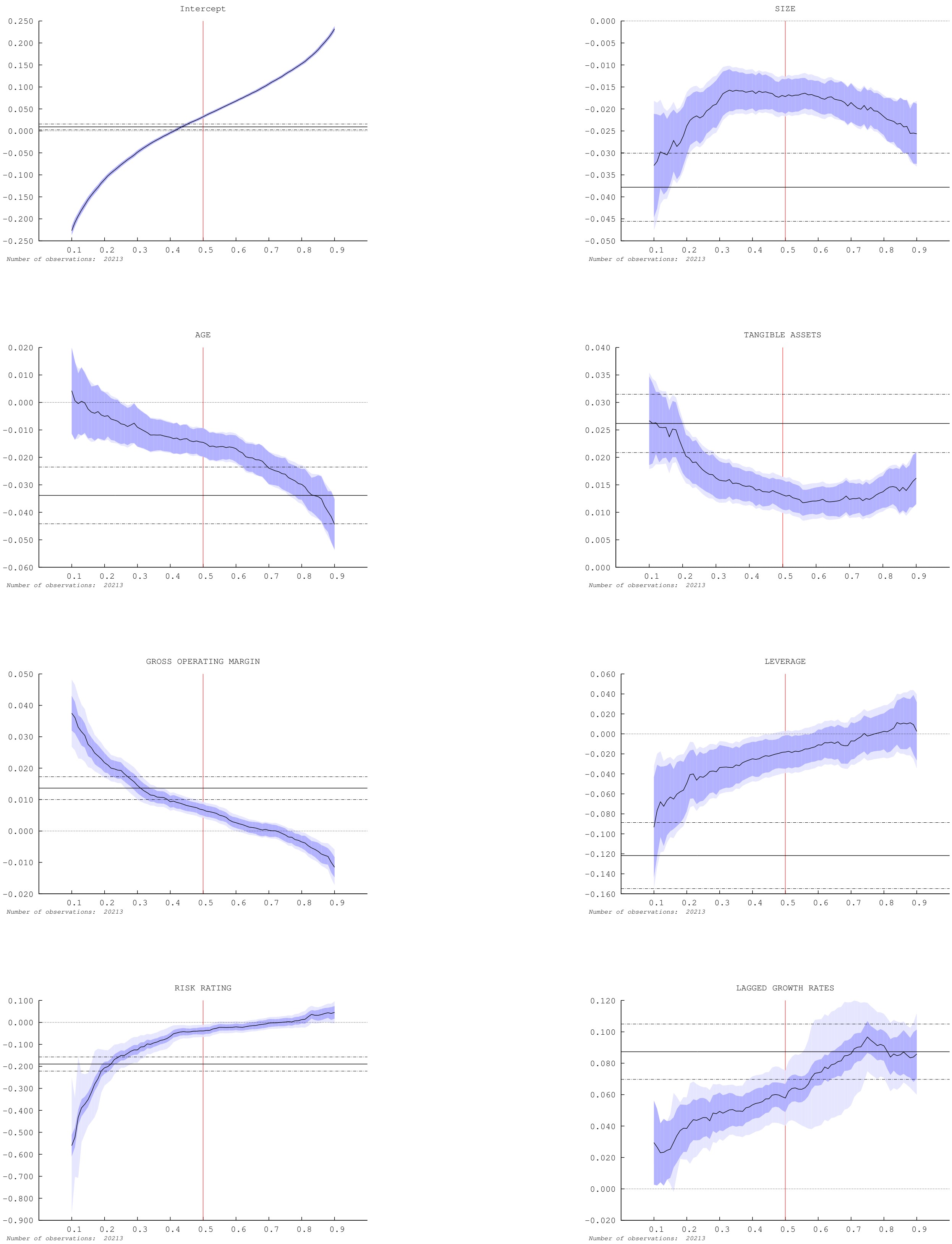

Figure 4: Quantile regression estimates of Equation 4 for 2003. Shadow bands represent 99% confidence intervals obtained using kernel approximation to the local density (light shadow) and the asymptotic covariance matrix assuming i.i.d. errors (dark shadow). OLS estimates are also reported (solid horizontal black line) with a corresponding 99% confidence band.

revenues; Age, defined as the number of active years; Tangible Assets and Gross Operating Margins, defined as the log of the balance sheet entries with the same name; Leverage as defined in Section 2, and the risk rating dummy RR considered in the previous section.[9] The results of the regression are reported in Figure 4.[10] All non-dummy variables (Size, Tangible Assets, Gross Operating Margin and Leverage) enter the regression as deviations with respect to their means. This is done to simplify the interpretation of the estimated coefficients. Indeed, after this transformation, the QR intercept α_θ becomes a "centercept": the inverse distribution function of the growth rates of the average firm, that in this case is a non risky firm with total sales of $7,654$ thousands of euros, an age of about 7 years, tangible assets and gross operating margins of $1,049$ and 371 thousands of euros respectively and a leverage of 0.31. The estimated intercept is reported in the top-left corner of Figure 4: both the shape and support appear as essentially unchanged with respect to the stylized model presented in the previous section. The other plots present the correlations by quantile for all the relevant regressors: they provide the change in the dependent variable $g_{i,t}$ associated with a deviation of a regressor from its mean. For instance, according to the picture in the top-right panel, if the firm's size is increased by 1, the associated change in growth rates is about -3% if the firms belongs to the first decile, -1.5% if it belongs to the fifth decile and about -2.5% if it belongs to the ninth decile.

The important first result that one gets by an overall inspection of Figure 4 is that the OLS estimates (thick horizontal black lines) provide an extremely poor description of the association of all the regressors with the endogenous variable. Basically none of the considered variables has a simple location-shift effect on the conditional distribution of growth rates. Moreover, confidence bands are small enough to suggest significant differences in the effect exerted across the different quantiles. Tangible assets and gross operating margin show a decreasing profile in their estimates across quantiles. This suggests a negative effects of these variables on the support of the growth rates distribution. Firms which are stronger in collateral or generate more cash flow tend to be less volatile, as a population, than firms with less collateral and a lower cash flow. The effect of gross operating margins is stronger and smoother. A similar pattern is observed for age: the distribution of growth rates for older firms has a lower support, which implies a less volatile growth pattern. Notice that the reduction of the variance of growth rates when firm size increases is a well documented phenomenon (see Bottazzi and Secchi, 2005, and references therein). Interestingly, in our specification, the effect is more attributable to age than to size itself, probably because of the strong correlation existing between the two. The increasing behaviour in θ for the estimates of leverage and risk rating, conversely, testifies for their "widening" effect on the conditional distribution of the dependent variable. Riskier firms and more leveraged ones display highly volatile behaviors, with more probable extreme growth events, both positive and negative. The effect of leverage is symmetric and relatively small, given the support of the variable (see the interquartile range in Table 1). The effect of the risk rating dummy, on the other hand, is strong and asymmetric. Revenue losses are indeed higher for risky firms, with a negative effect on growth rates reaching -0.6 for the first decile, that is an incremental reduction of revenues by about 50%. A similar impact, however, is not observed for positive growth rates: the estimates is not different from zero in the top 40% of the conditional distribution.

[9]Before applying the log to the GOM we replace its actual values with 1 whenever we observe negative figures. Since the Gross Operating Margin is used as a proxy of internal cash flow this transformation should not decrease its explanatory power.

[10]For brevity, we omit the estimate for $g_{i,t-2}$. Its inclusion would have added no further insight to the discussion.

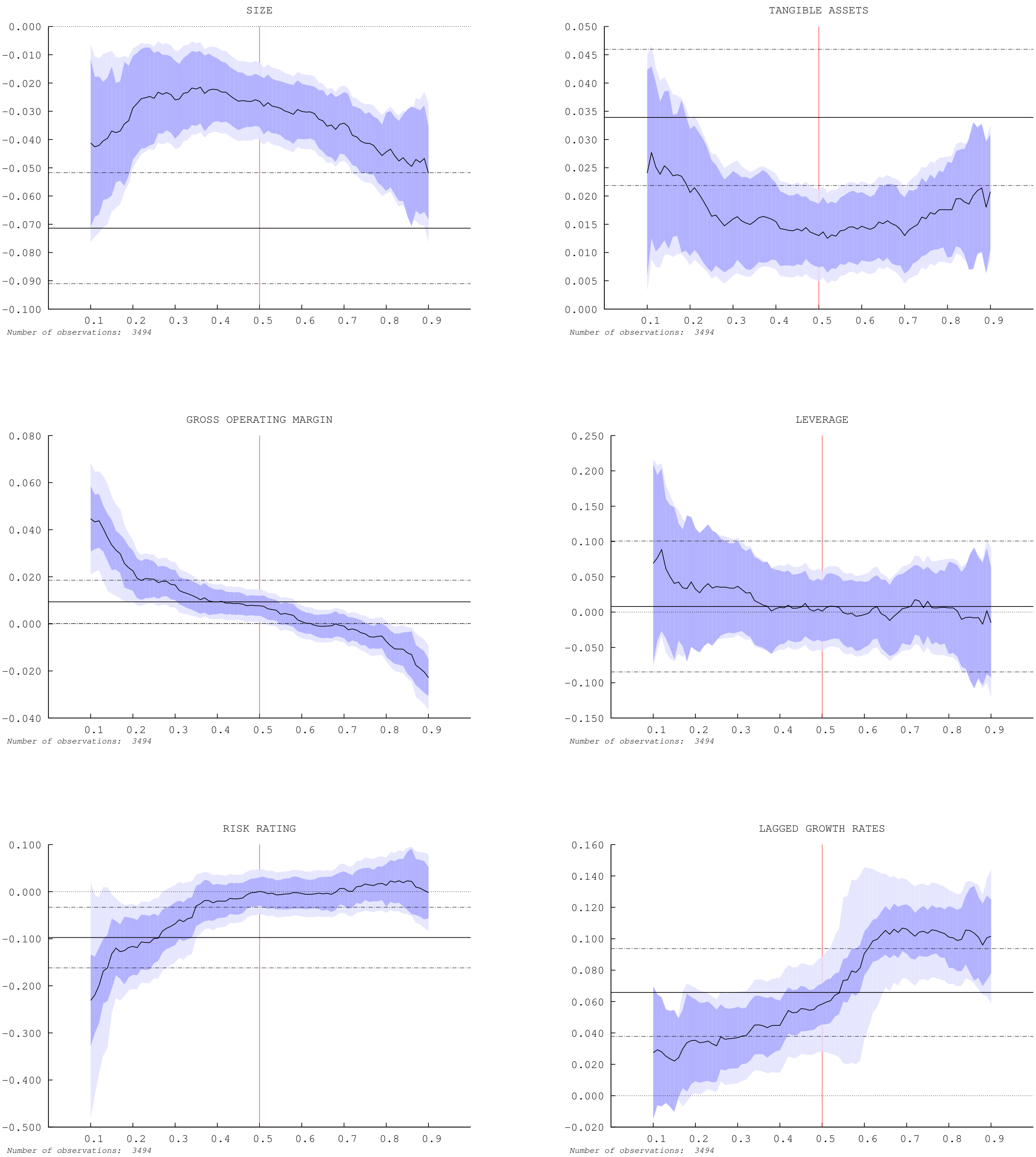

Figure 5: Quantile regression estimates of Equation 4 for young firms in 2003. Shadow bands represent 99% confidence intervals obtained using kernel approximation to the local density (light shadow) and the asymptotic covariance matrix assuming i.i.d. errors (dark shadow). OLS estimates are also reported (solid horizontal black line) with a corresponding 99% confidence band.

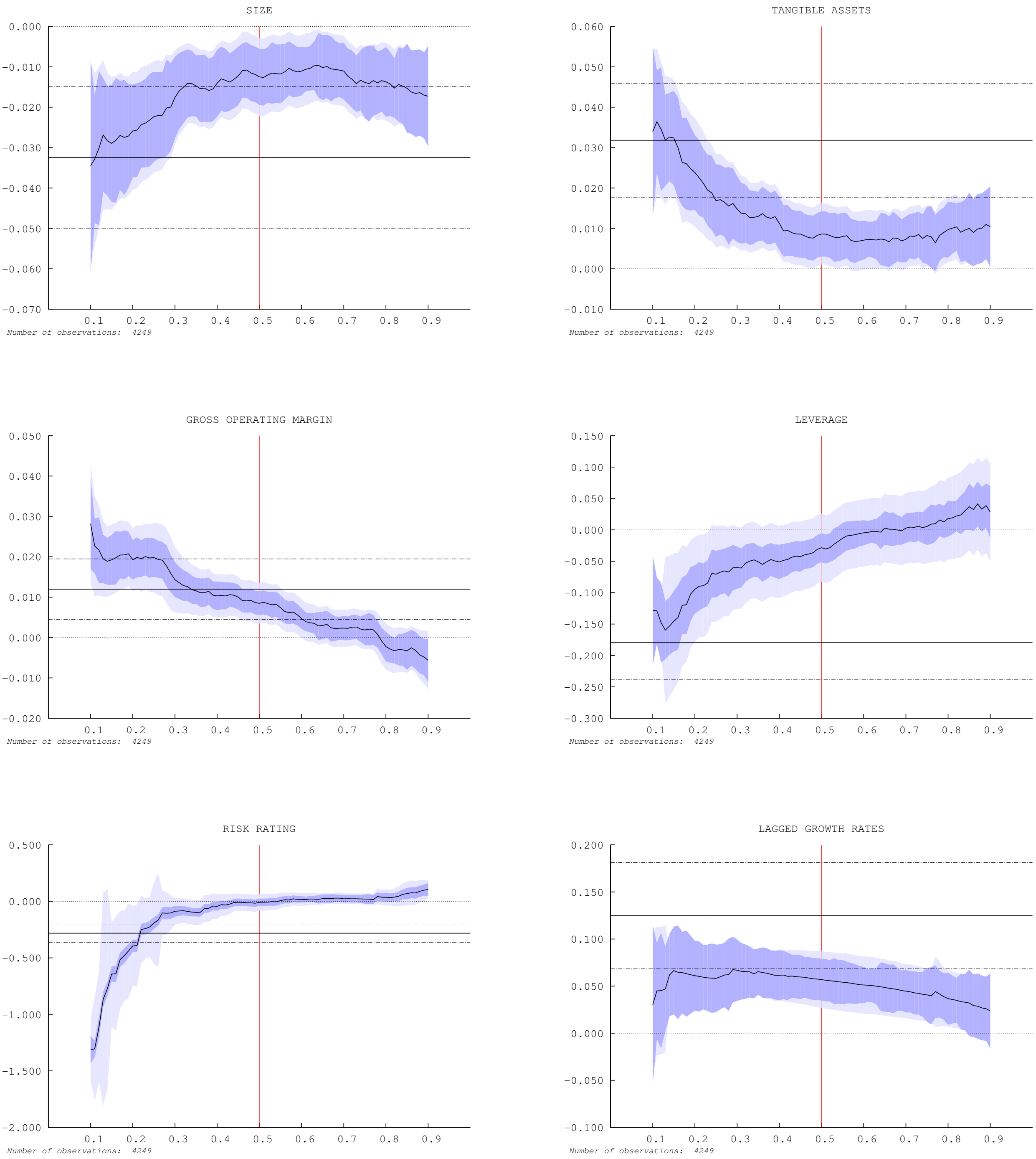

Figure 6: Quantile regression estimates of Equation 4 for old firms in 2003. Shadow bands represent 99% confidence intervals obtained using kernel approximation to the local density (light shadow) and the asymptotic covariance matrix assuming i.i.d. errors (dark shadow). OLS estimates are also reported (solid horizontal black line) with a corresponding 99% confidence band.

As mentioned in the Introduction, we are also interested in observing if the relationship between financial fragility and growth is different for young and old firms. In this respect, the significant effect exerted by age revealed by the results in Figure 4 constitutes a first evidence in this direction. We can obtain further hints by considering two sub-population of firms, the young and the old, as we did in the previous section. We regress the same model but considering only firms with less then 10 years of activity and firms with more than 30 years. The results are reported in Figure 5 and Figure 6 respectively. We obviously removed age from the regressors and we do not report the centercept, as our main interest rests in measuring the effect exerted by the explanatory variables. The two sub-samples have a reduced number of observations, precisely 3,494 young and 4,249 old firms. This is reflected in the increased width of the confidence bands. As can be seen, the results reveal significant differences between the two groups of firms. As expected, the effect of lagged size is less relevant for old firms. This confirms that the hampering effect that size exerts on growth has a non linear nature and tend to disappear when more mature and bigger firms are considered.[11] The effect of an increase in tangible assets is, in the lower deciles, similar for young and old firms. When larger growth rates are considered, however, the positive effect of the presence of collateral is significantly more relevant for young firms. The latter are also more sensitive to cash flow. Indeed the distributional shrinking implied by having operating margins above the average is stronger in the sub population of young firms. These results confirm the findings in Bottazzi et al. (2012) that young firms present higher sensitivity to aspects of their operating activities and asset structure which are likely to impact on the availability of external founds. Interestingly, the residual effect of leverage on growth, once one controls for all other variables, is negligible for young firms while it has a depressive effect on more mature companies. Different behaviors have also to be recorded for the risk rating. Risk seems to exert a stronger loss reinforcing effect on old firms: the lower tail of the distribution is stretched by a factor that, in the case of the first decile, reaches the remarkable level of -1.5, which implies that bad performing firms which are also classified as highly risky face a cumulative loss of revenues of about 80%.

5 Robustness checks

The model in the previous section was estimated only on year 2003. To investigate if the obtained results depend, at least in part, on some peculiar and transient features of the Italian economy in that year we perform the following check. We consider the model in Equation (4) dropping the autoregressive component and we estimate it on the three years available in our database, from 2001 to 2003. The results are reported in Figure 7, together with the original estimates of the main model in Section 4. The reported confidence intervals are those of year 2003. We again omit the intercept. Notice indeed that this would have been the only estimate affected by the introduction of an year dummy in the original model and is not relevant for our present purposes. As can be seen, the quantile estimates for the different years lay inside the 2003 confidence intervals for all the variables under investigation, apart Tangible Assets, for which a significant downward shift is observed in 2001. So, apart a possible shift in the centercept, the relationship between the explanatory variables and the dependent variable seems to be structural and persistent, at least in the considered time span. At the same time,

[11] Performing a nonparametric kernel regression of growth rates versus age, we observe that the effect of the latter on the expected value of the former basically disappears when firms older than 5-6 years are considered. Due to space constraints we do not insert this further check in the present paper. It is however available upon request.

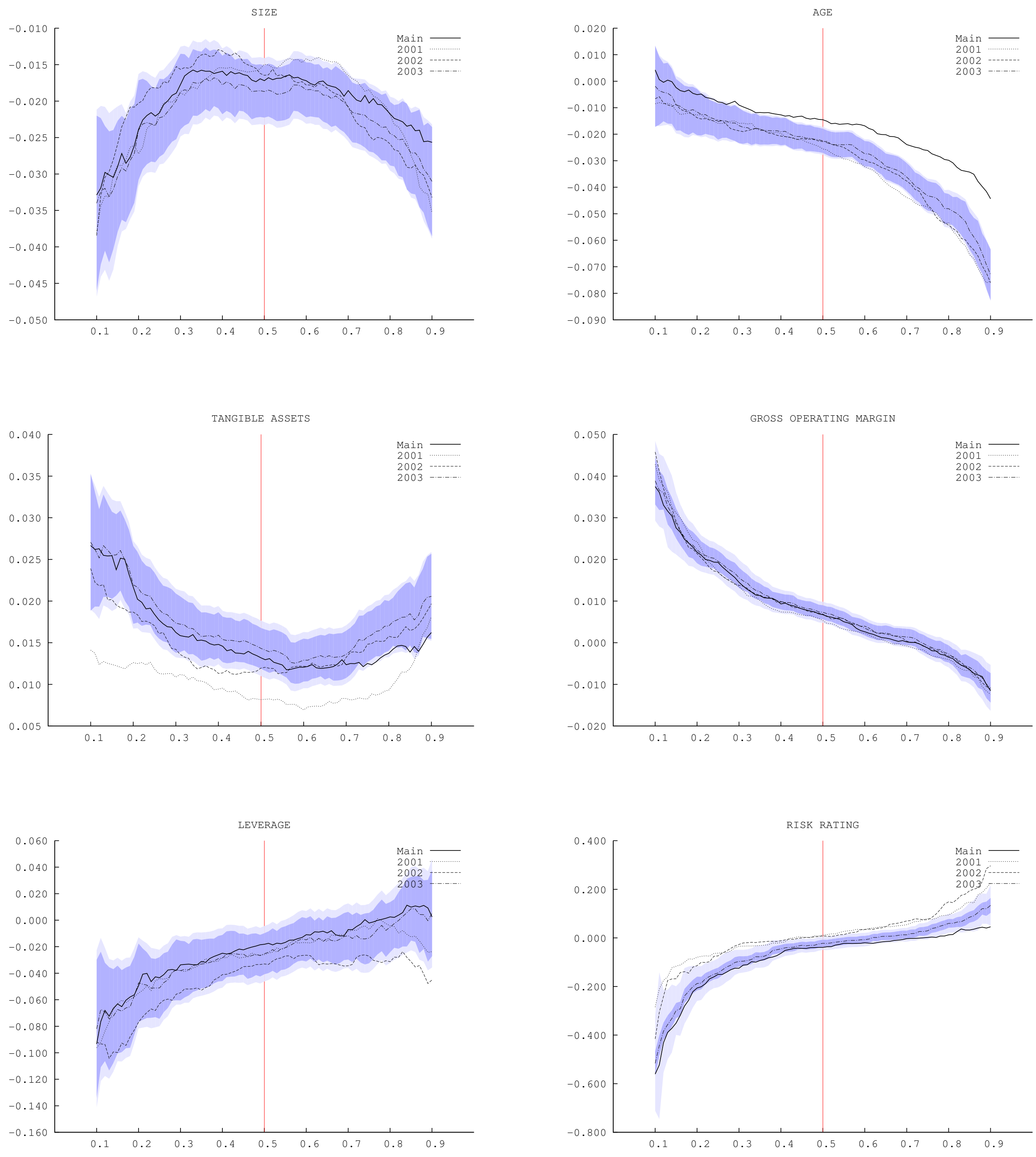

Figure 7: Quantile regression estimates of Equation 4 excluding the AR component in different years. Shadow bands represent 99% confidence intervals obtained using kernel approximation to the local density (light shadow) and the asymptotic covariance matrix assuming i.i.d. errors (dark shadow). Confidence interval refers to 2003. OLS estimates are also reported (solid horizontal black line) with a corresponding 99% confidence band.

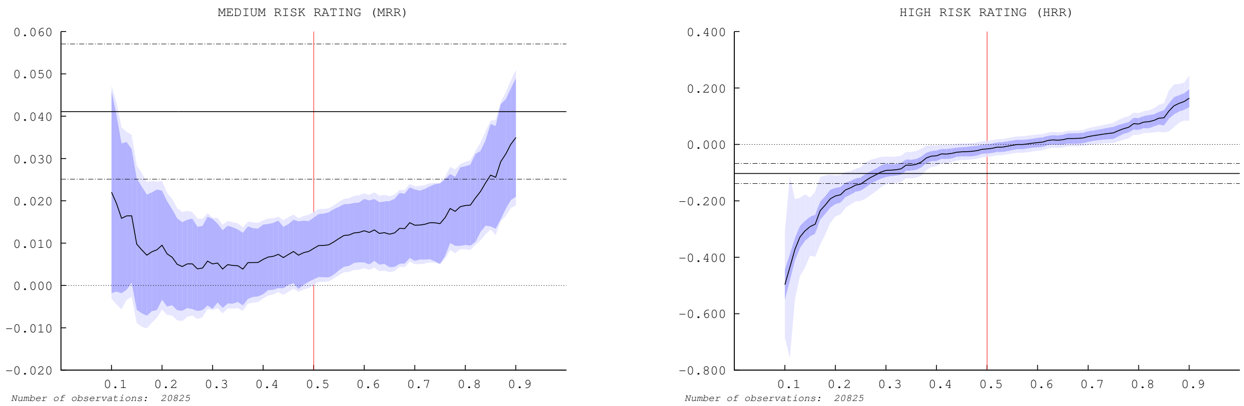

Figure 8: Quantile regression estimates of medium (MRR) and high (HRR) risk rating dummies in Equation 4 in 2003. Shadow bands represent 99% confidence intervals obtained using kernel approximation to the local density (light shadow) and the asymptotic covariance matrix assuming i.i.d. errors (dark shadow). COnfidence interval are based on 2003 observations. OLS estimates are also reported (solid horizontal black line) with a corresponding 99% confidence band.

the removal of the autoregressive part of the original model, notwithstanding its significance, does no change the estimates of the other variables. The only significant modification concerns age, and only in the top deciles.[12] This kind of robustness checks would have been impossible in an ordinary regression framework.

The effect of the Risk Rating variable RR in the model of the previous section was found to be substantial. Due to its somehow residual nature, it is particularly relevant to assess to what degree the specific definition of the RR dummy impacts on the obtained results. To perform this assessment we re-estimate the model in Equation (4) introducing two different dummies: a Medium Risk Rating dummy (MRR) and a High Risk Rating one (HRR). The first dummy is set equal to 1 if the CEBI risk rating index of the firm is between 1 and 4 included, and zero otherwise. The second dummy is equal to the dummy RR in the previous section. In general we find that the inclusion of two risk rating dummies instead of one does not change significantly the estimates of the other regressors in the model. However, the two dummies somehow interfere, as can be seen from the estimates reported in Figure 8. The newly introduced variable results significantly different from zero only for the upper half of the conditional growth rate distribution. The HRR dummy captures essentially the same effect of the risk rating variable RR in the original model, even if the impact in the highest deciles appears amplified.

Finally we re-estimate the model in (4) adding a set of sectoral dummies as defined in Section 2. No significant variations in the estimated coefficients are observed. We conclude that the findings of the previous section are confirmed also when different specifications and different samples are adopted.

[12]The modification of the age regressor translates in a similar modification of the size regressor if the model is estimated on small and large firms separately. This could be in part explained by a possible attrition bias in the sample selection, for which small firms tend to be more autocorrelated than large ones. In order to reduce this bias we re-estimate the model by dropping firms of age less than 2. No significant variation is observed in all relevant regressors. These results are available upon request.

6 Conclusion

We investigated the effect of a series of financial explanatory variables on the distribution of firms growth rate. The variables were selected to capture different aspects related to firm access to financial resources, both internal and external, like the flow of cash, the amount of collateral and a general index of credit soundness. In addition we controlled for size and age. To solve, at least partially, the endogeneity problem, the lagged growth rate was added among the explanatory variables. In order to capture the distributional effect of these variables we adopted a quantile regression framework.

First and foremost, by comparing the estimates obtained via quantile regression with a traditional OLS approach, we showed that none of the variables considered exerts a simple location-shift effect on the distribution of growth rates. In particular, the estimates obtained through OLS are often extreme and not representative of the central tendency. This is a consequence of the sensitivity of this methodology to the presence of outliers and extremal values. The QR was able to reveal both a support-enhancing and a support-reducing effect. Responsible for the former are variables like leverage and risk-rating, while the latter effect is observed for older and bigger firms.

We then analyzed two sub-samples, considering only young and only old firms, respectively. We found that the effect that the different financial variables exert on the conditional growth rate distribution is different for the two groups. The growth rate of old firms is mainly affected by leverage and, for those already troubled, by the affect of being assigned a high risk rating. Conversely, young firms growth rates rely more heavily on the capability to generate cash flow. For these firms the leverage is still relevant but it exerts a support-reducing effect, so that more leveraged young firms behave less erratically than the less leveraged ones.

Finally, results based on the quantile regression framework turns out to be peculiarly robust. The effect of risk rating on growth rates estimated in Section 3 was only marginally modified by the inclusion of the set of other regressors which led to the model in Section 4. At the same time, the results of the latter model are basically unaffected by the exclusion of relevant explanatory variables, like the lagged growth rates. The wider spectrum of phenomena that we were able to identify using QR confirms the necessity to move beyond simple location-shift models when analyzing the determinants of complex economic phenomena like the growth dynamics of business firms.

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Policy implications

Relevance of financial constraints

Contrary to the prediction of economic theory, the capability of a firm to produce cash flow in the short run and the amount of assets it is able to provide as collateral might significantly constraint the financial credit it is able to receive and increase its cost. It seems clear the the Italian credit market faces huge difficulties in coping with the business evaluation and appropriate financing of firms, especially of the young ones. In periods of scarce or negative economic growth, when the demand contracts and the cash flow get reduced, the lack of an appropriate financing channel can lead to the forced liquidation of economic activities which have the potential to result profitable in the long run. In this respect, the intervention of external authorities aimed to promote industrial and commercial lending, creating the conditions for banks and other financial institutions to open, extend or renew their credit channels to firms, should be seen as a long run preservation and improvement of the economic capability of manufacturing and service sectors, rather than a short run distortion of the credit market.

Adoption of appropriate methods to measure the extent of the phenomenon

The impairing effect that financial constraints exert on the growth of firms has been largely underestimated in the past. As we show in this paper, one reason for this has been the adoption of econometric tools clearly inappropriate to investigate the issue. The widespread reliance on regression methods designed to provide only a measure of the shift in expected growth rates generated by financial constrains has in fact concealed the stronger effect that these constraints exert on the tail of the distribution. Indeed firms which are already shrinking are much more severely affected by credit rationing than firms which are expanding. As we have shown in other contributions (see for instance G. Bottazzi, A. Secchi and F. Tamagni "Productivity, Profitability and Financial Performance", Industrial and Corporate Change, 17, pp.711-751, 2008) however, the conditional growth rates of firms on the short run has little correlation with their long run profits and even less with technical efficiency. We strongly recommend to regulatory bodies and statistical offices the adoption of distribution-based econometric techniques, like the quantile regression we use in this contribution, to measure the extent of financial constraints and asses their economic impact.

Industrial policy geared toward entrants and young firms

The comparison of the effect of financial constraints on young and old firms we performed in our contribution leads straightforwardly to the conclusion that young firms are particularly exposed to credit rationing as their access to external finance depends too strongly on their capability to generate cash flow in the short run. This is what one would expect in a credit market in which lenders are short horizon investors with a weak screening capability. The economic losses that such a credit market can potentially generate, in terms of missed opportunities and inefficient allocation of capital, are huge. Any intervention of the regulatory bodies, central and local administrations, to soften the dependence of young firms on cash flow and collateral in order to access external finance should be welcomed. These interventions can include the adoption of mixed public/private credit channels, the introduction of risk-sharing agreements with industrial associations and of better screening practice in the banking sector.